# Title:

Estimation of Medical Diagnostic Likelihood Ratios Using Artificial Intelligence

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**Conflicts of Interest**

B.W.L. claims an equity interest in Mountain Biometrics, a startup focused on machine learning medical time series data.

**Description:** (1-2 sentences)

Large language model-estimated diagnostic likelihood ratios showed negligible bias bounded dispersion with 700 literature-reported likelihood ratios, demonstrating their potential to supply auditable evidence weights for Bayesian reasoning in clinical diagnosis.

# Abstract: (\*\*\*/300 words)

*Introduction*

Accurate, context-appropriate likelihood ratios (LRs) are required to apply Bayesian reasoning in clinical diagnosis, yet empiric LRs are scarce because diagnostic test accuracy studies are costly and onerous to perform. Large language models (LLM) may be able to estimate diagnostic LRs by drawing on indirect or inferred clinical associations.

*Methods*

We compared LLM-estimated LRs from three OpenAI models (GPT-4o, o3, GPT-5) with all literature-reported values curated by TheNNT.com. A few-shot prompt was served to each LLM to elicit numerical LR estimates. Agreement was evaluated using Bland-Altman analysis for mean bias and multiplicative limits of agreement.

*Results*

We compiled 700 literature-reported LRs for 30 conditions. Most involved signs/symptoms (59%), historical elements (19%), or test results (16%). Reported LRs clustered near 1 (geometric mean 1.21, interquartile range 0.7 to 2.2). All models showed negligible mean bias. GPT-5 had the narrowest 95% limits of agreement (0.26x to 3.7x) versus o3 (0.23x to 4.28x) and GPT-4o (0.23x to 4.53x). GPT‑5 limits were significantly narrower than o3 and GPT‑4o (P < 0.001 for each comparison). Agreement varied by finding type, with laboratory test LRs varying more from reported estimates than history, signs/symptoms, or imaging.

*Conclusions*

Modern LLMs can estimate diagnostic LRs with very low bias and bounded dispersion, with newer models produce estimates more closely approximating values from the literature. These results indicate a significant potential for integrating generative AI into clinical diagnostic and educational workflows, particularly in situations where empirical data is limited, outdated, or unavailable.

# Introduction:

Medical diagnosis requires integrating history, examination, and test findings to identify the condition that best explains a patient’s presentation1,2. Bayesian reasoning has long been promoted as the normative framework for this task because of its simplicity, information efficiency, and broad applicability3–5. Instruction in Bayesian methods can improve trainees’ diagnostic reasoning6, yet its influence on medical education and daily practice remains modest. Most clinicians and educators continue to rely primarily on intuition, heuristics, and pattern recognition.7,8

An important barrier to broader use of Bayesian reasoning at the bedside and in medical education is the lack of accurate, context-specific diagnostic likelihood ratios. Likelihood ratios quantify how the presence or absence of a finding (historical element, symptom, examination finding, or test result) changes the odds of disease3,4. However, diagnostic accuracy studies are difficult to perform and interpret9,10, and true likelihood ratios often vary substantially by clinical context11. As a result, reliable likelihood ratios for findings in many common situations remain unknown and Bayesian reasoning cannot be effectively applied.

Recent advances in *generative* artificial intelligence might help. Large language models (LLMs) are neural network–based systems trained on large text corpora that can encode clinical knowledge and concept associations12,13. Unlike traditional machine-learning approaches that require task-specific training data, LLMs can sometimes generalize to novel tasks without prior examples via zero-shot or in-context learning14,15. Recent work suggests that LLMs can assist or parallel physician reasoning with surprising accuracy16–18, but adoption remains limited by persistent errors, opacity, and low trust among clinicians and patients.

One way to address this may be to task LLMs with performing individual, inspectable components of the diagnostic reasoning process. LLMs may be able to estimate diagnostic likelihood ratios by leveraging learned implicit associations, even when empirical data are scarce or non-existent. Accurate LR estimation could enable more widespread and effective use of Bayesian reasoning in both medical education and clinical practice. To test this possibility, we assess the accuracy three increasingly modern LLMs against published likelihood ratios drawn from the literature.

**Methods:**

We conducted a comparative study assessing the agreement between diagnostic LRs generated by three LLMs and empirically derived LRs reported by theNNT.com (© The NNT Group, 2010–2022). This study utilized public available data and did not involve human subjects, thus exempting it from institutional review board oversight.

### Reference Standard Likelihood Ratios

On April 1, 2025, we compiled a reference-standard dataset of likelihood ratios (LRReported) from theNNT.com a resource aggregating diagnostic likelihood ratios from published medical literature to assist with diagnostic reasoning. Point estimates for all LRs from all conditions listed on theNNT.com were either recorded, or derived as the geometric mean when only a range was provided (e.g. 1.5, 95% CI 1 – 2 would be coded as 1.5, while a range from 1 to 2 would be recorded as 1.41..). LRs were initially extracted using an automated script and then manually validated with duplicate independent review (PC and BWL). Each LR was categorized as a patient historical element, a sign/symptom, a test result, an imaging finding, and/or a diagnostic adjudication (e.g. “diagnosis based on ultrasound”). Scores (e.g. Centor criteria for Strep pharyngitis) were counted as each of the constituent findings. We qualitatively describe the strength of findings as strong (LR- ≤ 0.10 or LR+ ≥ 10), moderate ( 0.1 < LR- ≤ 0.2 or  5 ≤ LR+ < 10), weak (0.2 ≤ LR- < 0.5 or 2 ≤ LR+ < 5), or negligible (0.5 < LR < 2), consistent with prior literature3,4.

### Comparator Likelihood Ratios

On August 25, 2025, we generated comparator likelihood ratios (LRLLM) for all findings listed on theNNT.com using a constrained, few-shot prompting procedure. To represent a range of model ages, complexity, and inference costs, we queried three OpenAI LLMs (OpenAI, LP; San Francisco, California, USA) using the OpenAI API: GPT-4o (model release Nov 20, 2024), o3 (release Apr 16, 2025), and GPT-5 (release Aug 7, 2025). A full description of the prompting strategy is included in the supplement. In brief, the system prompted defined the LR as ‘P(finding | diagnosis) / P(finding | not diagnosis)’, gave qualitative LR strength descriptions3, and required an only-numerical response. We used 8 (non-reasoning model, GPT-4o) or 2 (reasoning models, o3 and GPT-5) clinician-estimated few-shot examples. These were clinician-estimated finding-clinical state-LR groups that were not in the evaluation set. Inference settings were temperature = 0.2 (non‑reasoning model) and ‘reasoning effort’ = "medium" (reasoning models); text.verbosity = "low" was applied where supported (GPT‑5 only). Internet search was not enabled for any models. No model fine-tuning was performed.

### Statistical Analysis

We assessed the agreement between reported likelihood ratios (LRReported) and LLM-estimated likelihood ratios (LRLLM) using Bland-Altman analysis19 on log-transformed LR values, as strength of evidence is additive on the log scale4,20. We calculated multiplicative (ratio) limits of agreement, which indicate the range within which LRLLM is expected to lie within an x-fold difference of the LRReported in 95% of cases. 50%, 75%, 90%, and 99% limits of agreement are also tabulated in the supplemental materials.

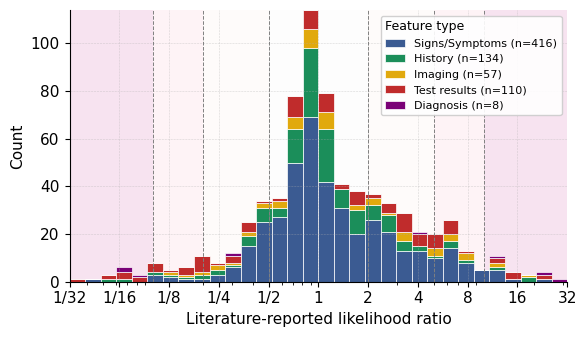
We compared models using paired t-test for mean differences (bias) and the Pittman-Morgan test for differences in the width (variance) of the limits of agreement21,22. Subgroup analyses were conducted by information type (historical element, symptom/sign, examination finding, test result, or diagnostic adjudication), and by direction of evidence (positive: LR >1; negative: LR < 1) using Welch’s t-test for bias and Levene’s test for differences in width. Agreement between qualitative LR strength categories (e.g. strong, moderate, weak)3,4 was assessed using Cohen’s Kappa with quadratic weights, which penalizes large disagreements more heavily and approximates squared-error on the underlying likelihood ratio scale23,24. Statistical significance was set at α = 0.05 without adjustment for multiple testing.Analyses were conducted in Python 3.11.11 and Microsoft Excel. Code is available at <https://github.com/reblocke/llm_estimate_lrs> .

# Results:

700 LRReported exploring the 30 available medical conditions were compiled from theNNT.com. Signs/symptoms were the most common type of LR (59%, n=416), followed by historical element (19% , n=134) and test results (16% , n=110)

LRReported’s ranged from 0.01 to 145.9, with a median of 1 (interquartile range 0.7 to 2.2) and a geometric mean of 1.21. Figure 1 shows the distribution of strength of evidence in the LRReported. Most (n=400) findings offered negligible strength of evidence (0.5 < LR < 2; 56.5%), with the next most common being weak evidence in favor of a diagnosis (n=120, 17.4%), weak evidence against (n=60, 8.7%) and moderate evidence for (n=52, 7.5%). Diagnoses tended to provide the strongest evidence, while signs/symptoms were the weakest (Supplemental Table 1).

**Figure 1:** Distribution of likelihood ratios reported in the literature, as collected from theNNT.com. Background shading represents strong, moderate, weak, and negligible strength of evidence categories3,4. Most of the LRreported cluster near 1, showing they offer negligible or weak evidence.

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Three sets of LRLLM were generated (for GPT-4o, o3, and GPT-5) for each of the 700 LRReported. Figure 2 shows the 95% multiplicative limits of agreement. All 3 models showed excellent mean bias (GPT-4o 1.02x, o3 0.99x, GPT-5 0.99x; no differences in pairwise comparisons). LR estimates from GPT-5 had the narrowest limits of agreement to the values reported on theNNT.com (95% limits of agreement from 0.26x to 3.7x, *P* > .001 vs both O3 and GPT-4o ), followed by O3 (0.23x to 4.28x), and GPT-4o (0.23x to 4.53x, *P* = .58 for O3 vs GPT-4o). Other coverage ranges (50, 75%, 90%, and 99%) are presented in the supplementary materials.

A diagram of a number of data

AI-generated content may be incorrect.

**Figure 2: Agreement between literature-reported and LLM-generated likelihood ratios:** Each panel shows the agreement between reported and model-generated likelihood ratios (LRs). The y-axis shows the log ratio (reported/model), and the x-axis shows the geometric mean of paired LRs. Solid black lines represent mean bias; Dashed lines indicate the multiplicative (i.e. x-fold) range in which 95% of estimates would be expected to be from a value reported on theNNT.com. Narrower coverage intervals represent closer agreement, and deviations of the mean line from unity indicate systematic bias. Shaded areas indicate the confidence intervals on each bound of agreement. All models showed negligible bias. GPT-5 had the tightest agreement with reported likelihood ratios.

Figure 3 shows the limits of agreement by finding type. Estimates of the strength of evidence followed similar patterns across models. Estimates of the importance of sign/symptoms, historical elements, and imaging findings were all similarly accurate, while test results agreed less closely with reported estimates.

A screenshot of a graph

AI-generated content may be incorrect.

**Figure 3: Agreement between LLM-estimated and literature-reported likelihood ratios** by type of clinical finding. Rows represent clinical finding categories (laboratory, imaging, history, sign-symptom, and diagnosis); columns represent LLM versions (GPT-4o, o3, and GPT-5). Categories were assigned by manual review, and likelihood ratios could be categorized as multiple types (e.g. scores integrating multiple findings).

When analyzed by the direction of evidence, patterns differed between models (Supplemental Figure 2). For GPT-4o, mean bias differed between negative (LRreported < 1) evidence (mean 1.13x) vs. positive (LRreported > 1) findings (mean 0.92x, *P* < .001). No difference in mean bias was observed for o3 (0.95x vs. 1.03x; *P* = 0.15). GPT-5 showed the opposite pattern of mean bias (negative evidence 0.88x vs positive evidence 1.12x; *P* < .001). The width of the limits of agreement did not differ by evidence direction for any of the models (GPT-4o *P* = .11; o3 *P* = .40; GPT-5 *P* = .37). For all 3 models, the calibration slope of predictions on the logarithmic scale suggested predictions were slightly less extreme than literature reported values (Supplemental Figures 2a-c)

Agreement between qualitative evidence categories was moderate for all models (Supplemental Figures 3a-c). The quadratic-weighted Cohen’s κ for GPT-5 was highest (0.775, 95% confidence interval [CI] 0.728-0.821), followed by o3 (0.745, 95% CI 0.702 – 0.789), and GPT4o (0.734, 95% CI 0.691 – 0.778).

# Discussion:

We found that LLMs estimated diagnostic LRs with negligible mean bias and bounded dispersion, with the newest model, GPT-5, showing the closest agreement with literature-reported values (95% limits of agreement of 0.26×–3.70×). Agreement varied by finding type, with laboratory test results showing looser agreement than history, signs/symptoms, or imaging results. Qualitative category agreement was substantial (κ = 0.78 for GPT-5*).*25 Together, these results suggest LLM-estimated LRs can support Bayesian reasoning when empirical LRs are absent, inapplicable, or uncertain.

Prior work shows that AI can augment human diagnostic reasoning by offering complementary strengths.26 Bayesian reasoning requires that likelihood ratios be known and sound, which often does not occur in practice.27,28 Our study provides, to our knowledge, the first large-scale evaluation of 700 finding–condition pairs across 30 conditions. We found that LLMs produced likelihood ratio estimates with very low bias and bounded dispersion across all categories. These findings suggest that LLMs could serve as a bridge in medical education and clinical workflows, enabling structured reasoning in situations where empirical LRs are unavailable.

Our study extends prior work by translating a component of LLM clinical reasoning into a quantitative unit, the LR4. In contrast to black-box outputs17, quantification enables auditing, supports teaching, and integrates cleanly with human or AI reasoning pipelines. Whether our observed limits of agreement are adequate depends on use case. It is likely too loose when a single, high-stakes finding would change a decision. Yet the negligible mean bias implies that serial Bayesian updating of multiple findings is expected to yield unbiased posterior probabilities if LR independence holds, a condition often violated but frequently close enough in practice to underly the strong performance of naïve Bayes machine learning methods29.

Strengths of this work include introducing a paradigm whereby LLMs diagnostic contribution is decomposed to one component of a clinical reasoning pipeline. We used a reproducible evaluation methodology across a broad set of comparators and multiple model generations and quantified agreement of both qualitative categories and continuous metrics. Both showed similar performance. Interestingly, using long-standing strength of evidence classification3, most of the empirically studied diagnostic features represented “negligible or weak evidence, underscoring that individual findings may generally be less diagnostic than creators of the classification scheme anticipated.

Several limitations warrant mention. We did not manually extract the LR confidence intervals or study-level clinical context from the primary literature compiled by theNNT.com, so our reference standards hide some uncertainty and models lacked the information needed to match the precise patient spectrum to which a given LR applies11. Similarly, we did not appraise the methodological rigor of the literature sources10. We report only estimates of agreement, and not a qualitative taxonomy of the types of errors LLMs made. Importantly, we are constrained to only benchmarking against reported values, so the reported LRs likely appear in model pretraining data. Although we observed no verbatim reproduction and disabled web search, the presence of the LRs could influence model weights in ways that are difficult to quantify but would generally lead to more precise agreement than on unseen data.30 Finally, besides following general best practices for prompt and context design, we did not fine-tune prompts or models to this evaluation to avoid overfitting. Refined prompting or retrieval-augmented estimates might further improve performance.

LLM-estimated LRs have several high-value uses. They could be used to address the “black-box” problem by providing auditable evidence weights for diagnostic reasoning. LLM-estimated LRs and LLM-estimated pretest probabilities, which have been found to be more accurate than clinician estimates31, could be used as inputs to explicit Bayesian updating algorithms, which are understandable to humans. More straightforwardly, they could be used as explanatory overlays to black-box outputs, though future work ensuring consistency would be required. In education, these estimated LRs could power automated scenario generation or structured reasoning checks in clinical-reasoning tutors. Most clinicians reason by gestalt, relying on intuition, heuristics, and pattern recognition that can be hard to transmit to learners7,32. Context-specific LRs could make those tacit cues explicit, enabling clearer teaching within the cognitive apprenticeship model32. With fit-for-purpose LR estimates, skilled educators could teach reasoning across a wider range of cases and clinicians could pair human judgement with AI in support of reflective practice and diagnostic calibration.33

Future work should test whether tighter specification of patient context and care setting improves the accuracy of LLM-estimated LRs. It should also measure how this context induces bias, and whether those biases mirror human decision-making.34 Comparative studies should benchmark the accuracy of LLM-estimates against clinicians across levels of diagnostic expertise. Determining whether LLMs can offer properly calibrated confidence assessments in their estimates would also be particularly valuable. Finally, didactic and clinical outcomes should be assessed when these tools are embedded into real workflows, measuring their influence on diagnostic accuracy, clinician cognitive load, and patient outcomes.

# Conclusion:

Modern LLMs can approximate diagnostic likelihood ratios with low bias and bounded dispersion, thereby enabling practical, auditable and potentially Bayesian updating to be applied to clinical reasoning.

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# Supplemental Materials

## Prompt Details

Code availability. The full pipeline for collating likelihood ratios (LRs) from TheNNT.com and generating large‑language‑model (LLM) estimates is available at: <https://github.com/reblocke/llm_estimate_lrs>

**Overview:** We prompted the LLMs to produce a single numeric likelihood ratio (LR) for a clinical finding with respect to a diagnosis, under a constrained output schema (only a numerical response) and with minimal verbosity.

**Prompt specification:**

* System role: “You are a Bayesian diagnostic assistant. Estimate a numeric likelihood ratio (LR) for a finding with respect to a diagnosis. Return only a JSON object matching the schema: {“value”: }, where value > 0.”
* Definition shown to the model: LR = P(finding | diagnosis) / P(finding | not diagnosis)
* Qualitative evidence bands provided as context. >10 strong for; 5–10 moderate for; 2–5 weak for; 0.5–2 negligible; 0.2–0.5 weak against; 0.1–0.2 moderate against; ≤0.1 strong against.
* Inputs to the model are plain text pairs: ”Condition: <diagnosis>\nFinding: <finding>”
* preceded by the system prompt, definition/bands, and few‑shot examples.

**Few‑shot strategy:** We include exemplar (Condition, Finding → LR) pairs to anchor scale:

* Non‑reasoning models (e.g., GPT‑4o): 8 examples.
* Reasoning models (o3 series; GPT‑5 family): 2 examples.

Example LRs were clinician‑estimated, not scraped values, to reduce the chance that exemplars appear in the evaluation set or anchor to relevant model pretraining data.

**Inference settings:**

* Non‑reasoning models: temperature = 0.2.
* Reasoning models: reasoning = {"effort": "medium"}; no temperature.
* Verbosity control: where supported (GPT‑5 family), text.verbosity = "low". The JSON‑only response format further suppresses extraneous text.

**Output schema and validation**:

* Schema. Structured output {"value": float}; parser enforces numeric type.
* Requests use the Responses API with a Pydantic schema (LRResponse { value: float }) to enforce structure.
* Validity rule. Accept only finite, strictly positive values.
* Retry logic. If the response is non‑numeric, malformed, non‑finite, or ≤0, the call is retried with exponential backoff and jitter until a valid LR is obtained (or up to the configured maximum, if set).

**Code:**

from \_\_future\_\_ import annotations

import os

import logging

from pathlib import Path

from typing import Optional

import time, math

from random import random

import pandas as pd

from pydantic import BaseModel

from openai import OpenAI

# -----------------------------------------------------------------------------

# 0) Configuration

# -----------------------------------------------------------------------------

logging.basicConfig(level=logging.WARNING)

client = OpenAI(api\_key=os.getenv("OPENAI\_API\_KEY"))

# Model registry:

MODEL\_CAPABILITIES = {

# GPT‑5 series (reasoning; supports text.verbosity; no temperature)

"gpt-5" : {"reasoning": True, "verbosity": True, "allow\_temp": False},

"gpt-5-mini" : {"reasoning": True, "verbosity": True, "allow\_temp": False},

"gpt-5-nano" : {"reasoning": True, "verbosity": True, "allow\_temp": False},

# GPT‑4.1 family (non‑reasoning; temperature OK); include snapshots + aliases

"gpt-4.1-2025-04-14" : {"reasoning": False, "verbosity": False, "allow\_temp": True},

"gpt-4.1-mini-2025-04-14": {"reasoning": False, "verbosity": False, "allow\_temp": True},

"gpt-4.1-nano-2025-04-14": {"reasoning": False, "verbosity": False, "allow\_temp": True},

# GPT‑4o family (non‑reasoning; temperature OK); prefer latest snapshot or alias

"gpt-4o-2024-11-20" : {"reasoning": False, "verbosity": False, "allow\_temp": True},

"gpt-4o-mini-2024-07-18": {"reasoning": False, "verbosity": False, "allow\_temp": True},

# o‑series (reasoning; no temperature)

"o3-2025-04-16" : {"reasoning": True, "verbosity": False, "allow\_temp": False},

"o3-mini-2025-01-31": {"reasoning": True, "verbosity": False, "allow\_temp": False},

"o4-mini-2025-04-16": {"reasoning": True, "verbosity": False, "allow\_temp": False},

}

MODELS = list(MODEL\_CAPABILITIES)

# -----------------------------------------------------------------------------

INPUT\_FILE = "nnt\_lrs\_processed.xlsx"

OUTPUT\_FILE = "nnt\_lrs\_with\_estimated.xlsx"

# -----------------------------------------------------------------------------

# 1) Prompt

# -----------------------------------------------------------------------------

SYSTEM\_CORE = """You are a Bayesian diagnostic assistant.

Estimate a numeric likelihood ratio (LR) for a finding with respect to a diagnosis.

Return only a JSON object matching the schema: {"value": <float>}, where value > 0.

"""

DEFINITION = """Definition:

LR = P(finding | diagnosis) / P(finding | not-diagnosis)

"""

BANDS = """LR evidence bands (reference):

>10 strong for; 5-10 moderate for; 2–5 weak for;

0.5–2 negligible;

0.2-0.5 weak against; 0.1-0.2 moderate against; ≤0.1 strong against"""

# Few‑shot examples - these are human guestimates (to avoid seeding the dataset and inflating performance)

FEW\_SHOT\_RICH = [

("deep vein thrombosis", "femoral vein noncompressaible on ultrasound", 16.0), # some data this might be higher?

("pericarditis", "pleuritic chest pain improved by leaning forward", 5.2),

("pulmonary embolism", "tachycardia >100 bpm", 2.2),

("urinary tract infection", "malodorous urine", 1.1),

("myocardial infarction", "enjoys playing chess", 1.0),

("appendicitis", "no RLQ tenderness", 0.45),

("pneumothorax", "bilateral lung sliding present on US", 0.18), # some data this might be lower?

("HIV infection", "4th‑generation Ag/Ab screen negative beyond window",0.05),

]

FEW\_SHOT\_MIN = [

("deep vein thrombosis", "femoral vein noncompressaible on ultrasound", 16.0),

("myocardial infarction", "enjoys playing chess", 1.0),

]

def build\_messages(diagnosis: str, finding: str, reasoning: bool) -> list[dict]:

msgs: list[dict] = [

{"role": "system", "content": SYSTEM\_CORE.strip()},

{"role": "system", "content": DEFINITION.strip()},

{"role": "system", "content": BANDS.strip()},

]

examples = FEW\_SHOT\_MIN if reasoning else FEW\_SHOT\_RICH

for dx\_ex, f\_ex, v\_ex in examples:

msgs.append({"role": "user", "content": f"Condition: {dx\_ex}\nFinding: {f\_ex}"})

msgs.append({"role": "assistant", "content": f'{{"value": {float(v\_ex)}}}'})

msgs.append({"role": "user", "content": f"Condition: {diagnosis}\nFinding: {finding}"})

return msgs

# -----------------------------------------------------------------------------

# 2) Structured Outputs schema (Pydantic)

# -----------------------------------------------------------------------------

class LRResponse(BaseModel):

value: float

# -----------------------------------------------------------------------------

# 2b) Retry wrapper (exponential backoff with jitter)

# -----------------------------------------------------------------------------

def estimate\_lr\_until\_positive(

diagnosis: str,

finding: str,

model: str,

client: Optional[OpenAI] = None,

max\_retries: Optional[int] = None, # None ⇒ retry indefinitely

base\_backoff: float = 0.5, # seconds

max\_backoff: float = 30.0 # seconds

) -> float:

attempt = 0

while True:

attempt += 1

try:

lr = estimate\_lr(diagnosis, finding, model, client)

if isinstance(lr, (int, float)) and math.isfinite(lr) and lr > 0:

return float(lr)

raise ValueError(f"Non‑positive or non‑finite LR: {lr!r}")

except Exception as e:

logging.warning(

f"[retry {attempt}] sheet finding='{finding[:80]}' | "

f"model={model} → {e}"

)

if (max\_retries is not None) and (attempt >= max\_retries):

raise

# exponential backoff with jitter

delay = min(base\_backoff \* (2 \*\* (attempt - 1)), max\_backoff)

time.sleep(delay \* (0.5 + random())) # 0.5–1.5× jitter

# -----------------------------------------------------------------------------

# 3) Estimator call (Responses API)

# -----------------------------------------------------------------------------

def estimate\_lr(diagnosis: str, finding: str, model: str, client: Optional[OpenAI] = None) -> float:

if client is None:

client = OpenAI()

cfg = MODEL\_CAPABILITIES[model]

msgs = build\_messages(diagnosis, finding, reasoning=cfg["reasoning"])

kwargs = {}

if cfg["reasoning"]:

kwargs["reasoning"] = {"effort": "medium"} # for GPT‑5 and o‑series

# no temperature/top\_p

elif cfg["allow\_temp"]:

kwargs["temperature"] = 0.2 # allowed for 4o / 4.1

# Apply verbosity only where supported (GPT‑5 family)

if cfg["verbosity"]:

kwargs["text"] = {"verbosity": "low"}

resp = client.responses.parse(

model=model,

input=msgs,

text\_format=LRResponse, # Structured Outputs → Pydantic

\*\*kwargs,

)

return float(resp.output\_parsed.value)

# -----------------------------------------------------------------------------

# 4) Main pipeline: read workbook → append model columns → write output

# -----------------------------------------------------------------------------

def run\_batch(input\_file: str | Path, output\_file: str | Path, models: list[str]) -> None:

sheets = pd.read\_excel(input\_file, sheet\_name=None, header=None)

for sheet\_name, df in sheets.items():

diagnosis = str(df.iloc[0, 0]).strip()

for model in models:

new\_header = "lr\_" + model

col = []

print(f"→ {diagnosis[:60]} | {model}")

for i in range(len(df)):

if i == 0:

col.append("") # top-left cell (sheet label row)

elif i == 1:

col.append(new\_header) # column header row

else:

finding = str(df.iloc[i, 0]).strip()

if not finding:

col.append("") # keep blank rows blank

continue

try:

# retry until a strictly positive, finite float is returned

lr = estimate\_lr\_until\_positive(

diagnosis, finding, model, client,

max\_retries=None # set to an int (e.g., 8) to cap retries

)

except Exception as e:

lr = "ERROR"

logging.warning(

f"Error on sheet '{sheet\_name}', row {i}, model {model} after retries: {e}"

)

col.append(lr)

# Insert as object dtype to accommodate strings like "ERROR"

df.insert(df.shape[1], new\_header, pd.Series(col, dtype="object"))

sheets[sheet\_name] = df

with pd.ExcelWriter(output\_file, engine="openpyxl") as writer:

for name, frame in sheets.items():

frame.to\_excel(writer, sheet\_name=name, index=False, header=False)

print(f"Done – results saved to '{output\_file}'")

if \_\_name\_\_ == "\_\_main\_\_":

run\_batch(INPUT\_FILE, OUTPUT\_FILE, MODELS)

## Supplemental Table 1: Distribution of Reported Likelihood Ratios, by type

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Statistic | Overall | Test results | Imaging | History | Signs Symptoms | Diagnosis |
| Count | 700 | 110 | 57 | 134 | 416 | 8 |
| Geometric mean | 1.206 | 1.071 | 1.322 | 1.065 | 1.267 | 1.164 |
| 5th percentile | 0.190 | 0.060 | 0.200 | 0.226 | 0.360 | 0.064 |
| 25th percentile | 0.700 | 0.312 | 0.680 | 0.755 | 0.700 | 0.077 |
| 50th percentile | 1.000 | 1.000 | 1.000 | 0.995 | 1.000 | 2.057 |
| 75th percentile | 2.200 | 3.675 | 3.300 | 1.675 | 2.100 | 16.300 |
| 95th percentile | 7.905 | 15.550 | 12.000 | 5.085 | 7.225 | 26.300 |
| Min | 0.010 | 0.010 | 0.010 | 0.050 | 0.040 | 0.060 |
| Max | 145.894 | 145.894 | 34.400 | 18.500 | 57.000 | 27.000 |

## Supplemental Figure 1: Limits of Agreement by Direction of Evidence

Rows separate positive (LRreported > 1) from negative findings (LRreported < 1).

A group of colored dots

AI-generated content may be incorrect.

## Supplemental Table 2: Coverage Intervals

Limits of Agreement that bound 50%, 75%, 90%, 95%, and 99% of model-generated likelihood ratios relative to literature-reported values. Intervals are expressed as multiplicative factors (“×”), indicating how far each model can be expected to deviate reported LRs. Parentheses show 95% confidence intervals for the estimate of each coverage limit.

**Model: gpt 4o**

|  |  |  |
| --- | --- | --- |
| Coverage | Lower edge (95% CI) | Upper edge (95% CI) |
| 50% | 0.61x (0.57x - 0.65x) | 1.70 (1.60x - 1.81x) |
| 75% | 0.42x (0.39x - 0.46x) | 2.44 (2.27x - 2.63x) |
| 90% | 0.29x (0.27x - 0.32x) | 3.56 (3.27x - 3.88x) |
| 95% | 0.23x (0.21x - 0.25x) | 4.53 (4.11x - 4.99x) |
| 99% | 0.14x (0.13x - 0.16x) | 7.24 (6.43x - 8.14x) |

**Model: o3**

|  |  |  |
| --- | --- | --- |
| Coverage | Lower edge (95% CI) | Upper edge (95% CI) |
| 50% | 0.60x (0.56x - 0.63x) | 1.64 (1.54x - 1.74x) |
| 75% | 0.42x (0.39x - 0.45x) | 2.33 (2.17x - 2.51x) |
| 90% | 0.29x (0.26x - 0.31x) | 3.38 (3.10x - 3.68x) |
| 95% | 0.23x (0.21x - 0.25x) | 4.28 (3.89x - 4.71x) |
| 99% | 0.14x (0.13x - 0.16x) | 6.79 (6.05x - 7.62x) |

**Model: gpt 5**

|  |  |  |
| --- | --- | --- |
| Coverage | Lower edge (95% CI) | Upper edge (95% CI) |
| 50% | 0.63x (0.59x - 0.66x) | 1.56 (1.47x - 1.65x) |
| 75% | 0.46x (0.43x - 0.49x) | 2.15 (2.01x - 2.29x) |
| 90% | 0.33x (0.30x - 0.35x) | 2.99 (2.77x - 3.23x) |
| 95% | 0.26x (0.24x - 0.29x) | 3.70 (3.40x - 4.03x) |
| 99% | 0.17x (0.16x - 0.19x) | 5.61 (5.05x - 6.22x) |

## Supplemental Figure 2 (a-c): Calibration Plots

LR’s are presented on the logarithmic scale.



## Supplemental Figure 3(a-c): Qualitative Agreement between LLMs and Literature-reported LRs



