MSR217

Evaluating a Large Language Model Approach for Systematic Literature Review Screening with Domain Expert Input

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Background

- Systematic reviews are crucial for synthesizing evidence for health technology assessments, and guiding clinical practice and policy[1]
- However, systematic reviews are time-consuming; this poses challenges for researchers to maintain up-to-date evidence in fast-moving fields[2]
- The growing volume of published studies has heightened demand for more efficient review methodologies
  - Automation tools (e.g., natural language processing) show promise in expediting study screening, data extraction, and quality assessment[3]
- Recent advancements in large language models (LLMs), such as OpenAI's GPT-4, offer potential to automate labor-intensive stages of reviews, improving both efficiency and comprehensiveness[4]

Objective

- To assess the performance of an LLM in conducting full-text screening for systematic reviews with domain expert input
- To determine the feasibility and reliability of LLMs in reducing manual workload and expediting the systematic review process while maintaining accuracy and quality in evidence synthesis

Methods

SYSTEM DEVELOPMENT

- Custom system using GPT-4o was developed to automate full-text screening process in systematic reviews aiming to accurately include or exclude studies based on Population, Intervention, Comparison, and Outcomes (PICO) criteria with minimal human involvement after initial setup phase
- **LLM Sherpa** facilitated parsing/interpretation of large text volumes,[5] breaking input into meaningful components for effective analysis of complex documents (e.g., scientific studies) with nuanced information dispersed across multiple sections
- Two-stage prompt approach with GPT-4o was used to enhance screening accuracy and transparency (**Figure 1**):
  1. **Stage 1: Understanding and Contextualization**
     - GPT-4o was provided research objectives and PICO criteria to build context for decision-making, allowing it to interpret relevant patterns
  2. **Stage 2: Decision-Making and Rationale Generation**
     - The model screened studies using context from Stage 1, providing a rationale for each inclusion/exclusion decision to ensure transparency

Figure 1: Workflow for Automated Screening

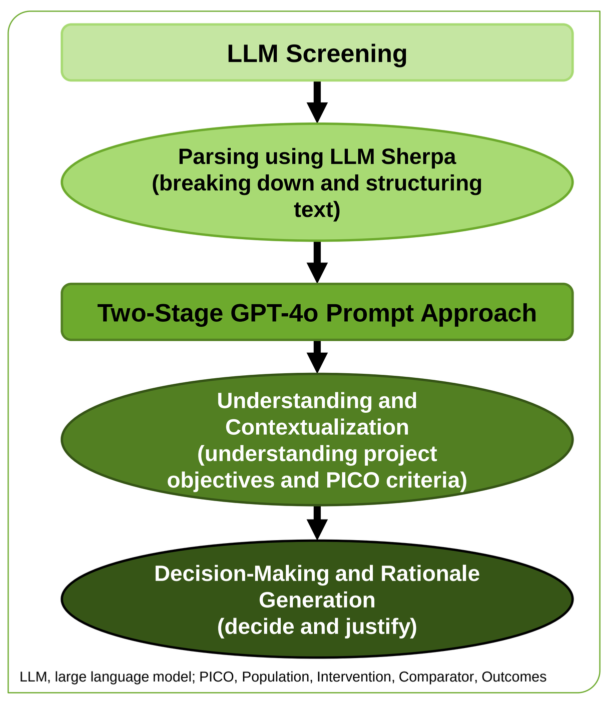
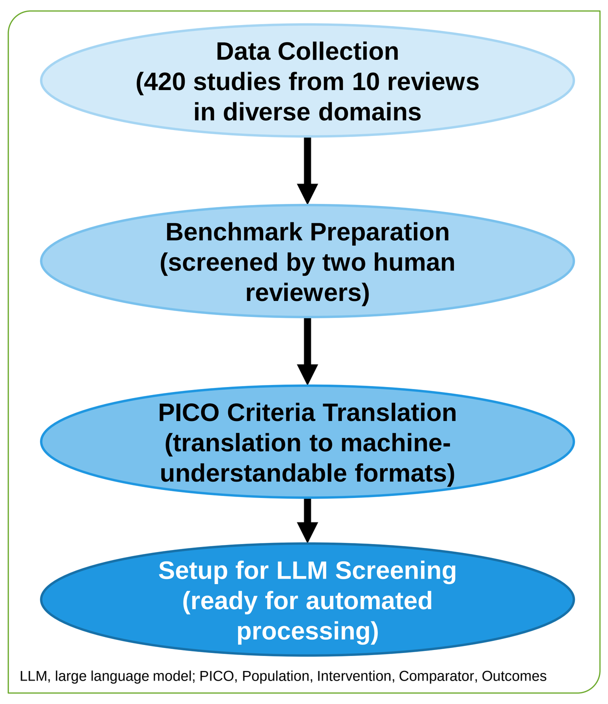


Figure 2: Pre-Screening Preparation



DATA SOURCES AND BENCHMARK FOR EVALUATION

- Final dataset of 420 studies from 10 systematic reviews across cardiology, dermatology, and oncology was used to evaluate performance of LLM
- Each study had been screened by two independent human reviewers, creating a reconciled "benchmark" dataset for reliable comparison of the LLM's decisions against human expert assessments (**Figure 2**)
- **Translation of PICO into machine-understandable formats**
  - PICO criteria were translated into structured, machine-readable formats by a domain expert to facilitate accurate interpretation by LLM; this format included explicit definitions for population, intervention, comparison, and outcome criteria of interest
- **Screening process with LLM**
  - GPT-4o model autonomously screened each study's full-text PDF for relevance based on PICO criteria
  - To ensure consistency, studies were removed from the screening process if they:
    - Were tagged as "duplicate publications" by human reviewers
    - Were excluded by human reviewers due to non-PICO-related reasons (e.g., full-text PDF could not be retrieved)

PERFORMANCE ASSESSMENT

- Performance of GPT-4o was assessed using key metrics[6]:
  1. **Sensitivity (Recall):** Model's ability to correctly identify relevant studies (true positives)
  2. **Positive Predictive Value (PPV):** Proportion of identified relevant studies that are indeed relevant (true positives among all positives)
  3. **Negative Predictive Value (NPV):** Proportion of identified irrelevant studies that are indeed irrelevant (true negatives among all negatives)
- System's output was compared with human screening results to assess agreement, inclusion/exclusion counts, and overall accuracy, as well as consistency, reliability, and generalizability
- Domain experts qualitatively assessed quality of LLM's rationales for inclusion/exclusion decisions to ensure alignment with PICO criteria and logical reasoning standards (**Figure 3**)
- The overall automation workflow is depicted in **Figure 4**

Figure 3: Evaluation and Comparison Process

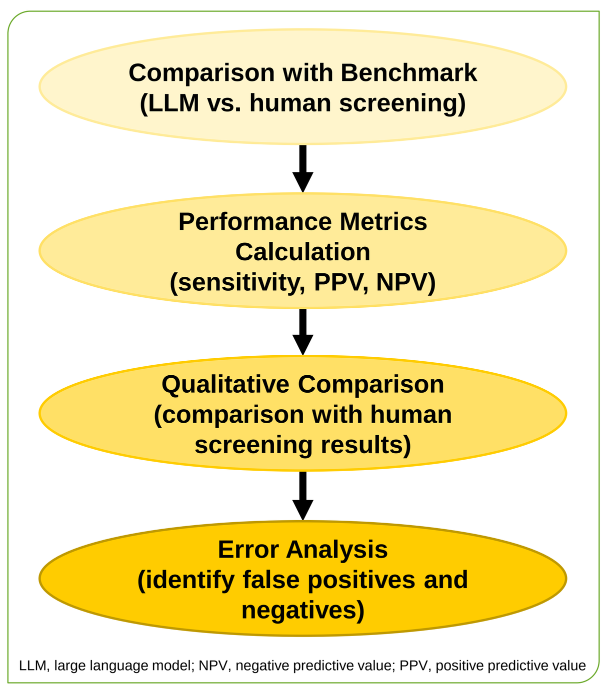
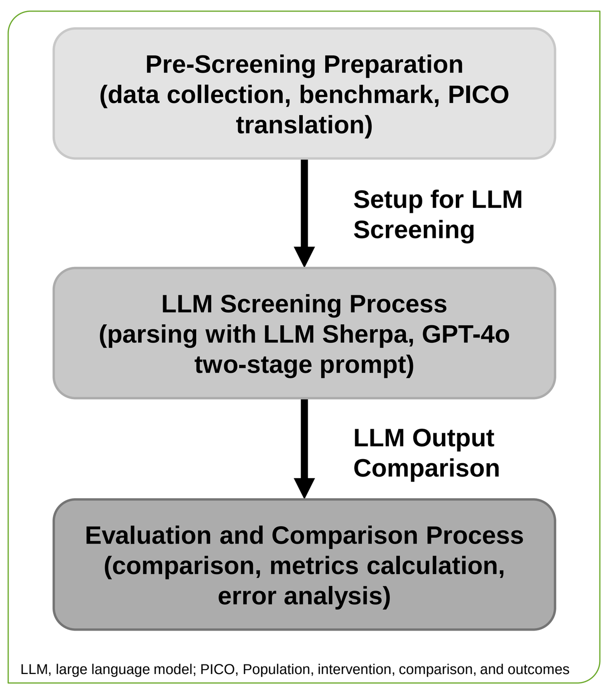


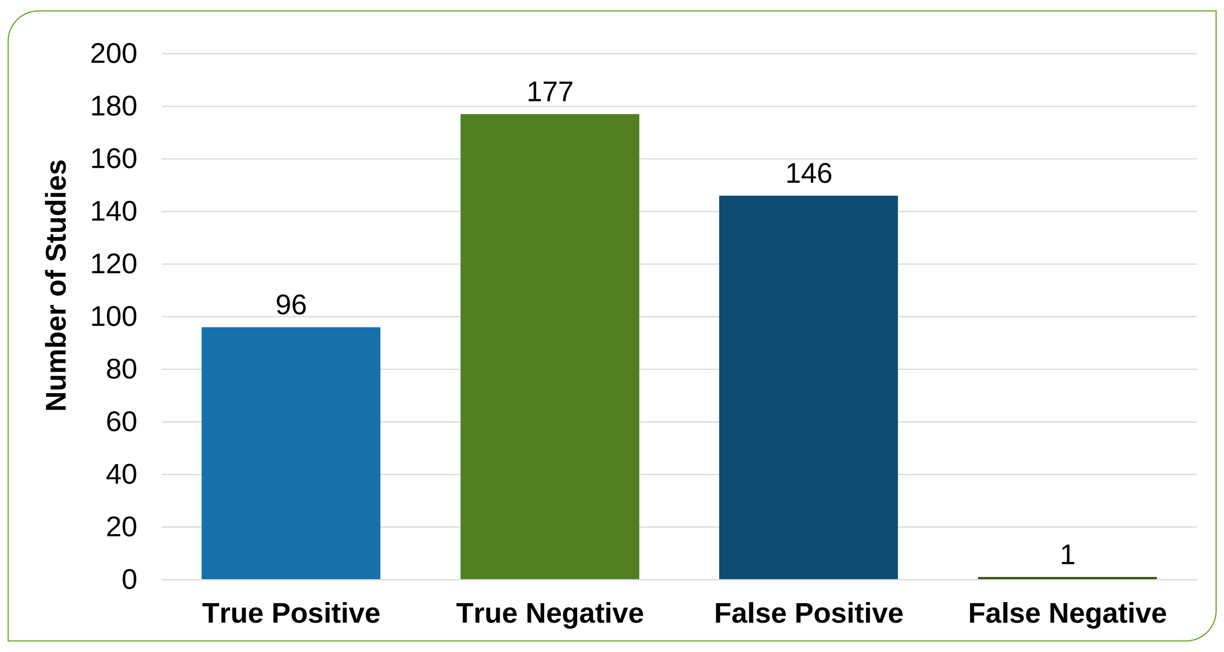
Figure 4: Overall Automation Workflow



Results

- Model showed **99.0% sensitivity** (96/97), effectively identifying studies that should be included in review (**Figure 5**)
  - High sensitivity ensures relevant studies are not overlooked; model is reliable for initial screening and contributes to a comprehensive review
- Model showed **39.6% PPV** (96/242) with 146 false positives identified, reflecting a tendency toward **over-inclusion** (**Figure 5**)
  - High false positive rate requires additional filtering of flagged studies, indicating the need for human review to ensure precision
- Model showed **99.4% NPV** (177/178), indicating **high accuracy** in identifying studies that should be excluded from review (**Figure 5**)
  - High NPV is crucial for minimizing unnecessary inclusions and reducing manual workload for human reviewers, especially in large-scale reviews
- LLM-based approach substantially reduced time spent screening, requiring only 20 minutes per 50 studies compared to 8 hours for a human reviewer (**Figure 6**)
- Thorough error analysis revealed **only one false negative**, underscoring the model's effectiveness in capturing relevant studies (**Figure 7**)

Figure 7: Error Analysis of False Positives and False Negatives



- **Justifications** for inclusion/exclusion were reviewed by domain experts and generally aligned with standard review practices
  - Model's ability to produce understandable and reasonable explanations enhances its utility in the screening process
  - Improves transparency and aiding human reviewers in validating or questioning model's decisions
- Hybrid model **combining LLM screening with human oversight** could provide optimal balance of efficiency and accuracy
  - The high rate of false positives emphasizes the importance of hybrid approach, ensuring balance of precision and recall
  - i.e., LLM would handle initial screening to exclude irrelevant studies; human reviewers would focus on refining final selection, significantly reducing manual workload in large-scale systematic reviews while upholding high standards for evidence synthesis

GPT-4o-based model showed high sensitivity (99.0%) and accuracy (NPV 99.4%) as a full-text study selection tool for literature reviews; time spent reviewing was reduced by 96%

Figure 5: Performance Metrics of LLM Screening

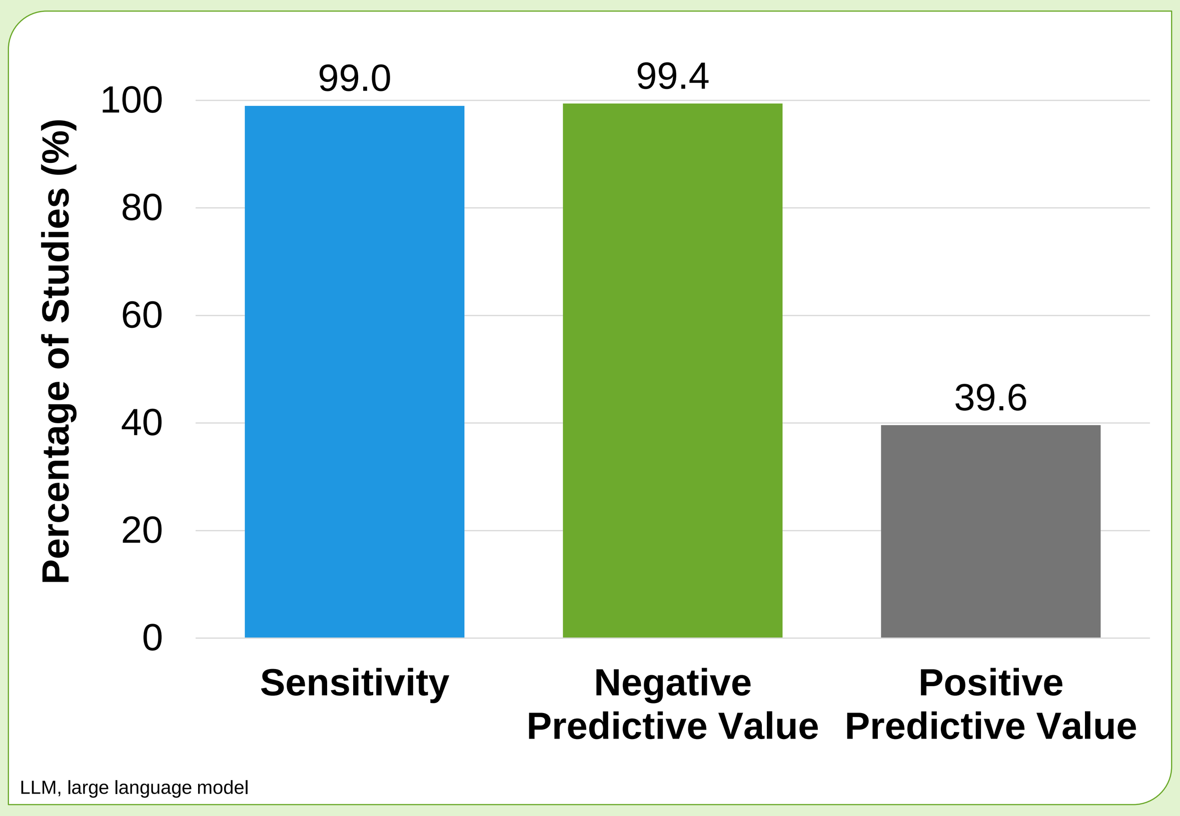
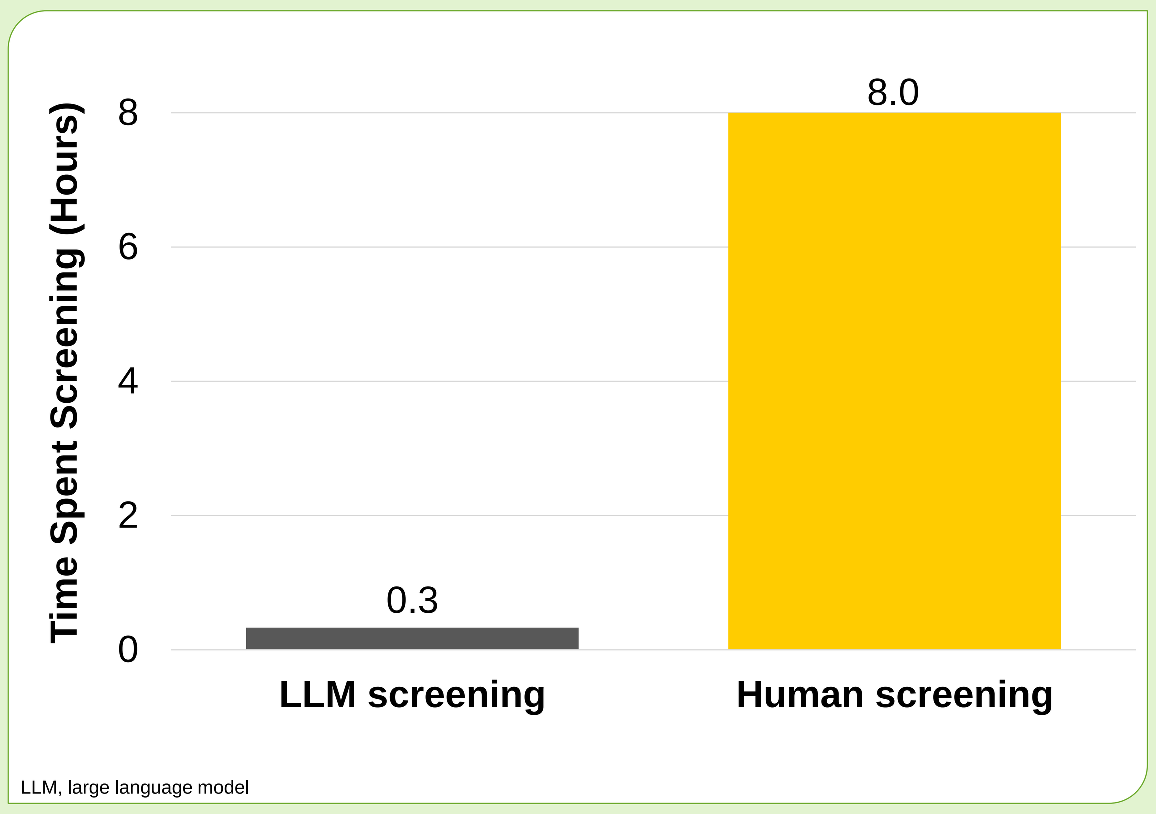


Figure 6: Time for LLM Screening vs. Human for 50 Studies



Conclusions

- Integration of GPT-4o for automating full-text screening in systematic reviews shows significant promise in alleviating the manual workload associated with large-scale reviews
- Model demonstrated high accuracy in exclusion decisions and robust sensitivity in identifying relevant studies, positioning it as a valuable tool in the initial screening stages
  - However, challenges such as over-inclusion and false positives highlight necessity for human oversight to ensure optimal screening
- A hybrid approach that combines LLM-driven automation with expert human review could optimize both efficiency and accuracy in the systematic review process

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