Assessing the Effectiveness of Large Language Models in Automating Systematic Literature Reviews: Findings from Recent Studies

MSR155

Value Analytics Labs

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BACKGROUND

- Systematic literature reviews (SLRs) are foundational for evidence synthesis in medical research but are often time-intensive and laborious. On average, completing a traditional SLR can take between 12 and 18 months and typically involves a team of at least three researchers.[1]
- Large Language Models (LLMs) offer potential for automating SLR tasks such as screening, data extraction, and bias assessment.
- However, the feasibility and performance of these models in conducting different steps of SLRs remain insufficiently documented.

OBJECTIVE

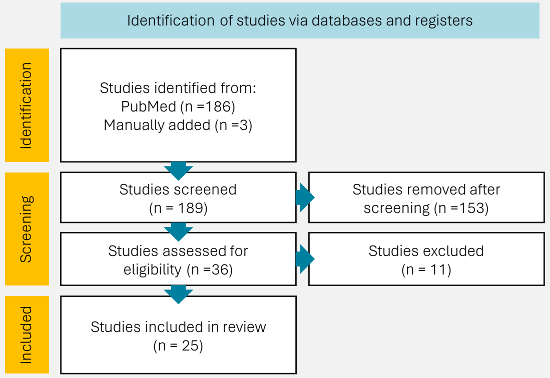
To evaluate the performance of LLMs across key tasks in the SLR process by reviewing recently published studies.

METHODS

We conducted a targeted literature review of studies applying LLMs in SLR workflows, focusing on performance metrics across multiple review tasks.

Study Identification: 25 studies published between Jan 2023 and Jan 2025 [2-26] (Figure 1)

Figure 1: *PRISMA Diagram for the Targeted Review of Studies applying LLM in SLR steps*



KEY FINDINGS

- LLMs show strong potential in automating key components of SLRs, particularly in early screening and data extraction.
- While different LLMs exhibit varying strengths and limitations across tasks, no study has comprehensively evaluated their performance across all SLR steps using AI.
- A hybrid approach that leverages the strengths of multiple LLMs may improve the overall efficiency and accuracy of SLRs.
- Performance of LLMs varies by task, suggesting that some steps in the SLR process may be more suitable for automation than others.
- Human oversight remains essential for conducting AI-assisted SLRs.
- Further research is needed to fully explore the capabilities and limitations of LLMs within SLR workflows.

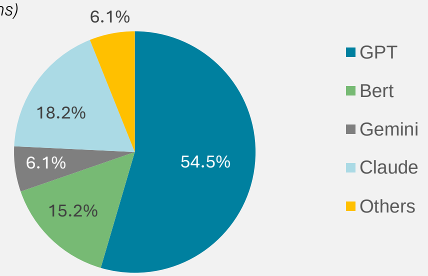
- **LLMs Assessed:** GPT, Gemini, Bert, Claude and others such as Google PaLM 2 and Meta Llama 2
- **SLR Tasks Analyzed:** Title and abstract screening, full-text screening, data extraction and bias assessment
- **Performance Metrics:** Sensitivity, specificity, accuracy, and inter-rater agreement (e.g., kappa score).

RESULTS

LLMs Assessed

Among all LLMs, GPT was the most frequently evaluated LLM across studies (Figure 2).

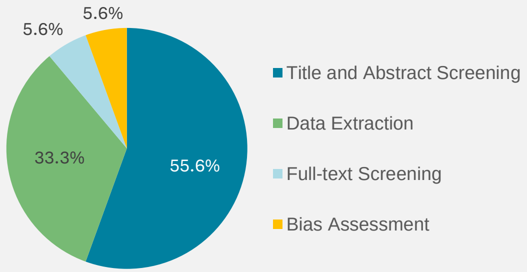
Figure 2: *Distribution of LLMs Evaluated (among 33 independent evaluations)*



Performance Evaluation

Among all SLR steps, title and abstract screening using LLMs was the most frequently evaluated one across studies (Figure 3).

Figure 3: *Distribution of SLR Tasks Evaluated (among 18 independent evaluations)*



LLMs demonstrated strong performance across various systematic review tasks (Table).

- **Title screening:** Sensitivity 94.3%–96.2%; specificity 85.5%–99.6%.
- **Abstract screening:** Accuracy 80%–97.5%; sensitivity 62%–95%; specificity 65%–98.7%.
- **Full-text screening:** Accuracy 87%; sensitivity 71.4%; specificity 93.8%.
- **Data extraction:** Accuracy 67%–96.3%; sensitivity 36%–96.2%; specificity >80%.
- **Bias assessment:** Strong agreement with human reviewers (kappa >0.89 for abstracts; 0.65 for full-text).

Table: *Performance of LLMs Across SLR Tasks*

Task	Best Performing Model	Metric	Performance Range
Title Screening	GPT-3.5	Sensitivity	94.3%–96.2% [18]
		Specificity	85.5%–99.6% [18]
Abstract Screening	GPT-4 (Acc, Spec) GPT-3.5 (Sens)	Accuracy	80%–97.5% [22, 26]
		Sensitivity	62%–95% [23, 26]
		Specificity	65%–98.7% [22, 23]
Full-Text Screening	GPT-4	Accuracy	87% [22]
		Sensitivity	71.4% [22]
		Specificity	93.8% [22]
Data Extraction	Claude 2 (Acc, Sens) GPT-4 (Spec)	Accuracy	67%–96.3% [14, 17]
		Sensitivity	36%–96.2% [14, 17]
		Specificity	>80% [17]
Bias Assessment	GPT-4	Kappa (Abstracts)	>0.89 [22]
		Kappa (Full-text)	0.65 [22]

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