

Expediting Evidence Synthesis: A Review of Recent Research Evaluating Artificial Intelligence's Performance in Evidence Synthesis and Summarization of Clinical Literature

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BACKGROUND

The annual rate of published research has grown steadily over the past decades leading to increasing volumes of available literature.¹

Synthesis of clinical literature can often be a time-consuming and resource-intensive process due to the number of publications that need to be reviewed, aggregated, analyzed, and interpreted.²

Artificial intelligence (AI) can potentially expedite the evidence synthesis process for health economics and outcomes researchers and is gaining traction for this use.

It is unclear, however, which AI tools are being used and whether they effectively improve the efficiency and quality of evidence synthesis.

OBJECTIVE

To review recent literature evaluating the performance of AI and large language models (LLMs) in the evidence synthesis of clinical research

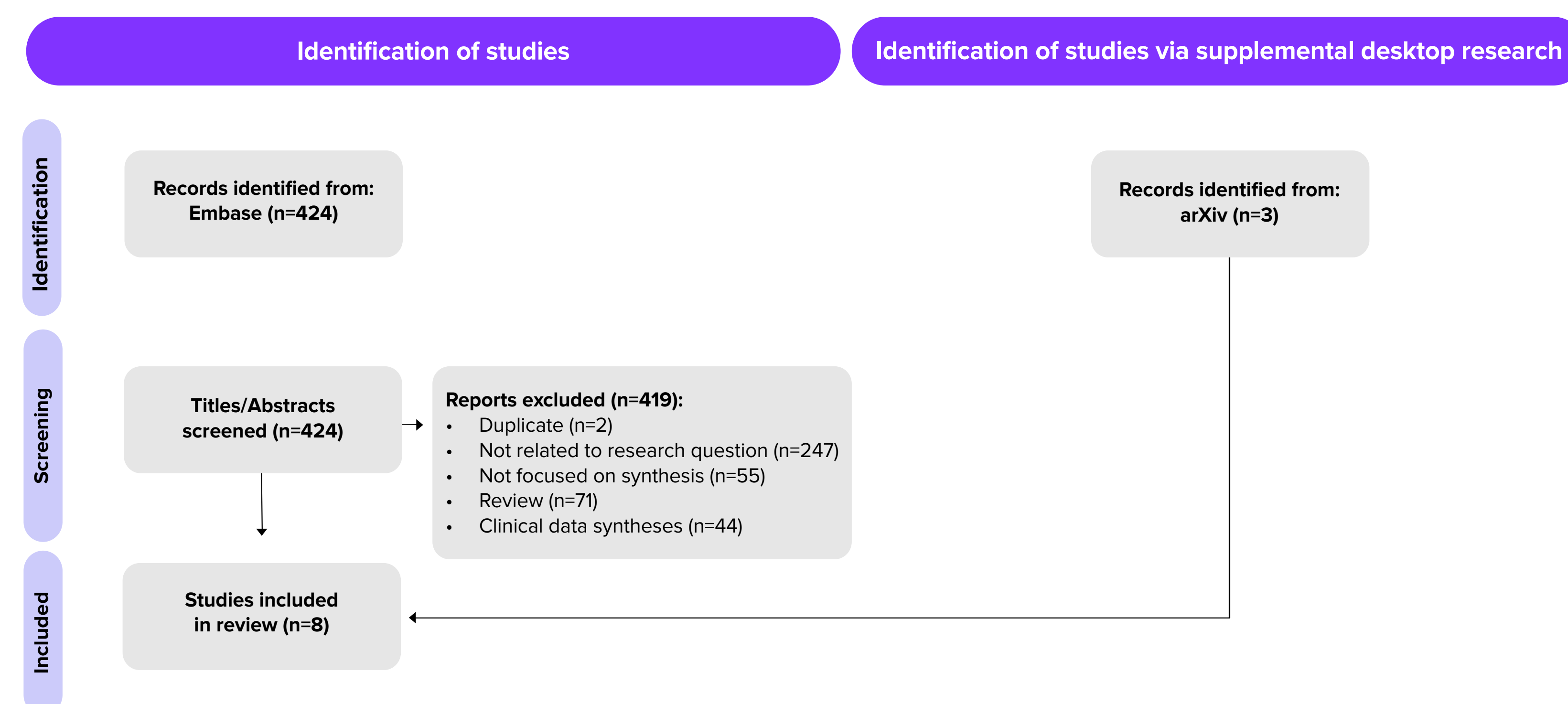
METHODS

A literature review was conducted in EMBASE for articles published since 2022 that describe the performance of LLM tools in clinical literature synthesis

Additional articles were identified through citation searching and supplemental desktop research on arXiv (Figure 1)

Key information was captured including the name of tools used, the type of evidence synthesized, and the methods for evaluating the tool's performance

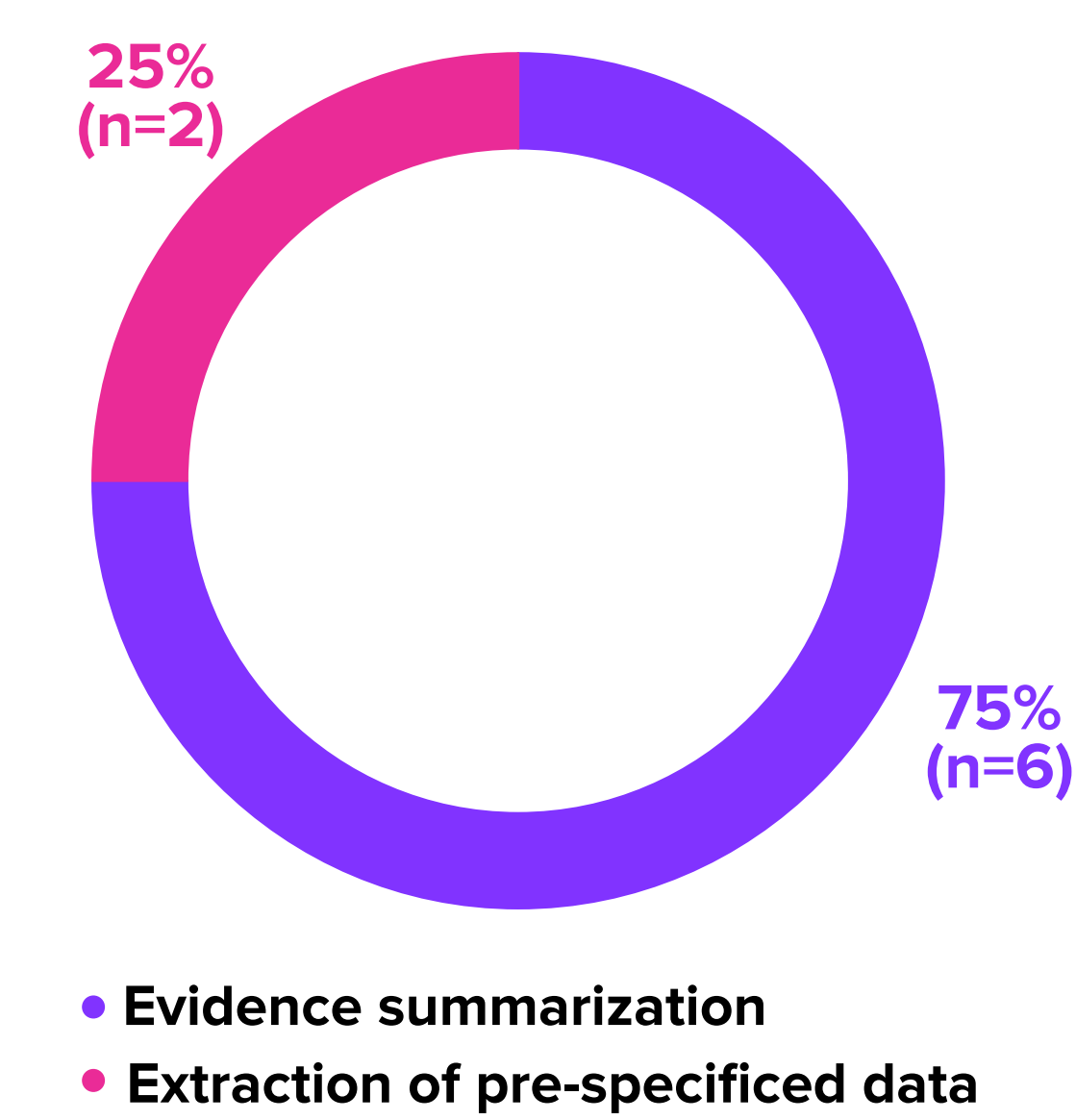
Figure 1: Search Breakdown



RESULTS

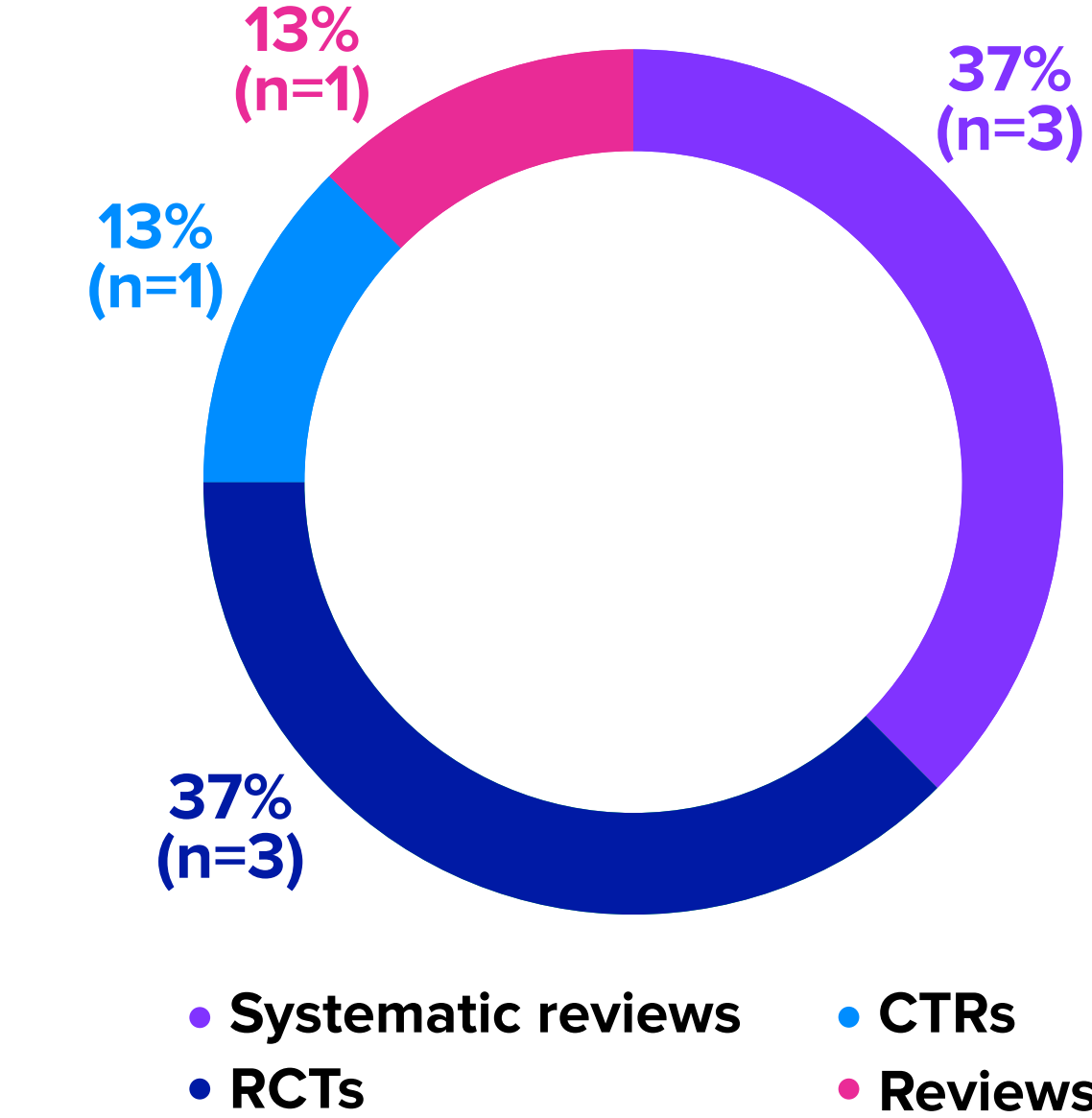
A total of 8 studies were identified; the majority (n=6) focused on evidence summarization, while the remaining 2 evaluated the extraction of pre-specified data (Figure 2)

Figure 2: Type of evidence synthesis assessed



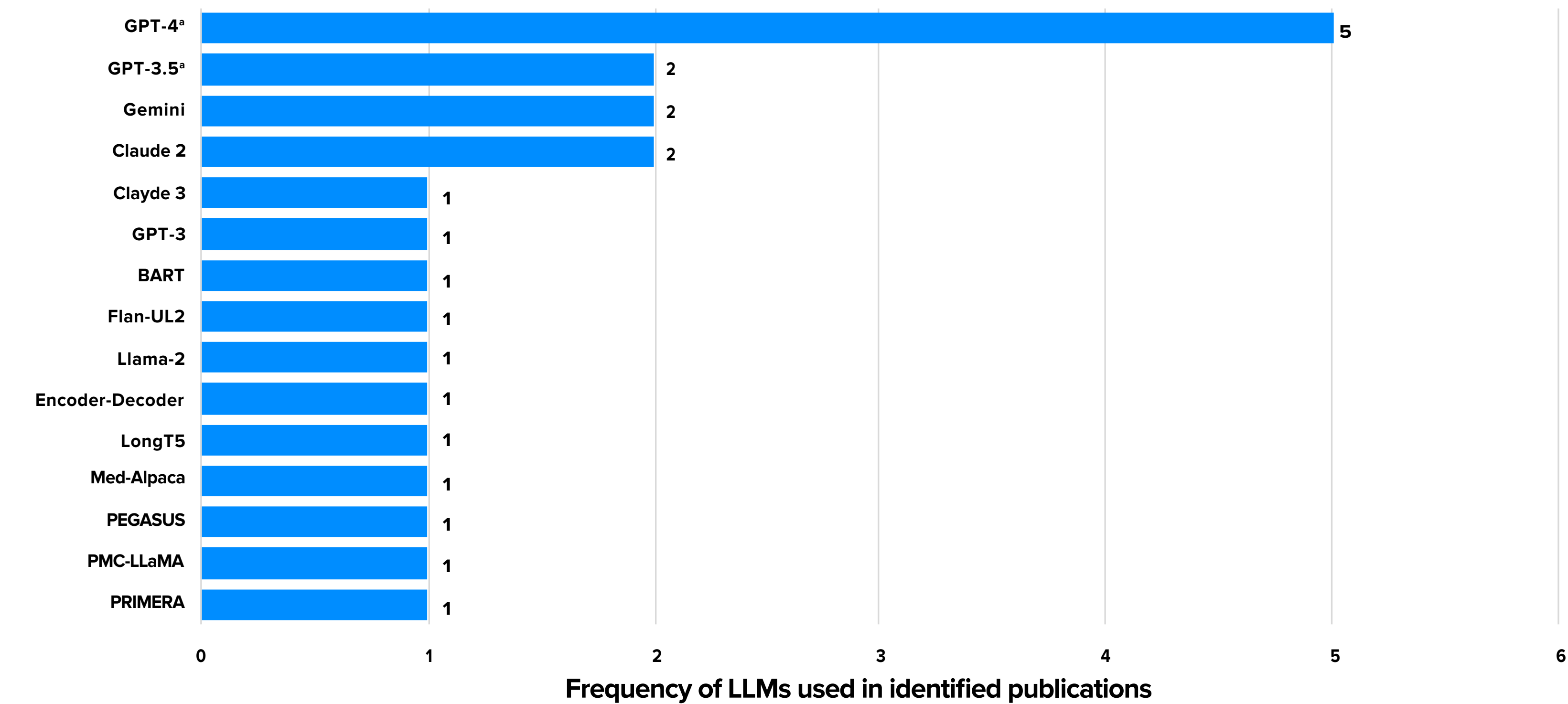
The clinical literature synthesized included systematic reviews (n=3), randomized controlled trials (n=3), clinical trial report (n=1), and review article (n=1) (Figure 3).

Figure 3: Type of literature synthesized



A total of 17 tools were identified, with some utilizing the same type of LLM (GPT-4), such as Ref AI,³ ScholarAI,³ and TrialMind.⁴ GPT-4 was the most commonly used LLM (Figure 4)

Figure 4: Types of LLMs used for the synthesis of clinical literature

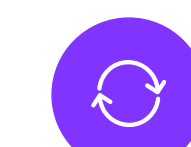


*Includes turbo version

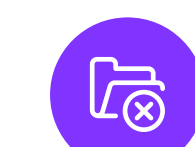
Assessments focused on



accuracy



comprehensiveness



missing data

Human evaluations of accuracy (n=4) resulted in the following scores (Table 1):

- Claude 2: 40%-97%
- GPT-4: 40%-87%
- Gemini: 44%-64%

Table 1: Overview of Assessment Methods

| Publication | Tools assessed | Type of evidence synthesis assessed | Type of literature synthesized | Type of assessment | Results of human evaluation |
|--------------------------|--|-------------------------------------|--------------------------------|---|---|
| Konet 2024 ⁵ | • Claude 2 • GPT-4 | Extraction of pre-specified data | RCT | Accuracy (human) | • Claude 2: 96.3% • GPT-4: 69% |
| Li 2024 ³ | • Ref AI (GPT-4 Turbo) • ChatGPT-4 • ScholarAI (GPT-4) • Gemini | Evidence summarization | Review | Accuracy, comprehensiveness, reference integration (human) | • RefAI: 83% • ChatGPT-4: 58.3% • ScholarAI: 62.7% • Gemini: 44% |
| Li 2024 ⁶ | • GPT3.5-turbo • GPT-4 • Gemini-1.0-pro • Flan-UL2 • Med-Alpaca • PMC-LLaMA | Evidence summarization | RCT | Precision, recall, accuracy (ROUGE, BLEU, METEOR) Completeness, correctness, coherence (human) | Correctness: • GPT3.5-turbo: 69% • GPT-4: 72% • Gemini-1.0-pro: 64% • Flan-UL2: 44% • Med-Alpaca: 44% • PMC-LLaMA: 45% |
| McMinn 2023 ⁷ | • Longformer-Encoder-Decoder • BART • PEGASUS | Evidence summarization | CTR | Accuracy (ROUGE, METEOR) | Not applicable |
| Shahib 2024 ⁸ | • GPT3 | Evidence summarization | RCT | Accuracy, coherence, usefulness (human) | Overall score was not generated for tool |
| Sun 2024 ⁹ | • Claude 2 • GPT-4 | Extraction of pre-specified data | Systematic reviews | Accuracy (human) | • Claude 2: 46-97% • GPT-4: 40-87% |
| Wang 2024 ⁴ | • TrialMind (GPT4+-Claude3.5) • GPT-4 | Evidence summarization | Systematic reviews | Accuracy (human) | Win rate* (across 5 studies) • TrialMind: 62.5%-100% • GPT-4: 0%-37.5% |
| Zhang 2024 ¹⁰ | • PRIMERA • LongT5 • Llama-2 • GPT-3.5 | Evidence summarization | Systematic reviews | Precision, recall, accuracy (ROUGE-L, METEOR) Consistency, comprehensiveness, specificity, readability (human) | Win rate* • LongT5: 60% • Llama-2: 59% • PRIMERA: 55% • GPT-3.5: Not reported |

*Ratio of summaries evaluated as better for each respective tool

^bRatio of machine-generated summaries evaluated as better than the baseline

DISCUSSION

The use of AI will continue to revolutionize how research is conducted, resulting in increased efficiency. Human oversight remains vital for validation and addressing errors.

Potential time savings can lead to cost reduction that can provide additional support for other activities to bolster a biopharmaceutical product's value story.¹¹

Due to variations in assessment methodologies across studies, no single LLM tool was identified as the definitive choice for evidence synthesis. However, as AI tools continue to evolve, improvements in accuracy and completeness are anticipated in the future.

CONCLUSION



In this review, GPT-4 was the most commonly tested tool. Future assessments should also quantify the potential time and cost saving through AI.



Numerous methods of assessment were observed, highlighting the need for a standardized assessment checklist to appropriately appraise the performance of LLM tools in evidence synthesis.



With the release of newer models (eg, GPT-4.5, Claude 3.7), continued assessment of AI tools will be essential to determine the feasibility of broader use in research.

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ABBREVIATIONS IN TABLES AND FIGURES

AI, artificial intelligence; CTR, clinical trial report; LLM, large language model; RCT, randomized controlled trial.

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CONTACT INFORMATION

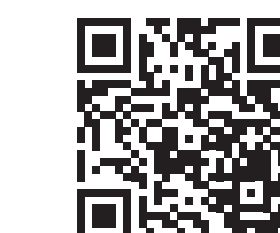
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