

Development of an AI-Powered Tool to Accelerate and Enhance Systematic Literature Reviews for Evidence-Based Decision-Making in Clinical Research

Authors: Paul Loustalot¹, Boris Kopin¹, Sacha Levy¹, Basile Ferry¹, Vincent Martenot¹

Affiliation: ¹Quinten Health, Paris, France

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INTRODUCTION

- Systematic literature reviews (SLR) are essential for synthesizing scientific evidence, particularly in clinical research. These processes remain highly time-consuming and labour-intensive due to the need to screen large volumes of publications.
- Traditional methods, such as BM25-based search engines or manual filtering, often fail to achieve satisfactory coverage without extensive manual review¹.
- This limitation underscores the need for hybrid approaches combining artificial intelligence (AI) and human validation to improve efficiency and accuracy.
- Advances in Natural Language Processing (NLP) and the emergence of Large Language Models (LLMs) have demonstrated remarkable capabilities in automating text processing tasks². Several works report time savings up to 68.5% and improved precision and consistency compared with traditional approaches^{3,4}.
- Full automation remains limited by challenges in achieving comprehensive coverage and generalizability comparable to expert review. Consequently, hybrid approaches integrating human oversight are essential, leveraging the speed of LLMs, while preserving the interpretative rigor of experts⁵.

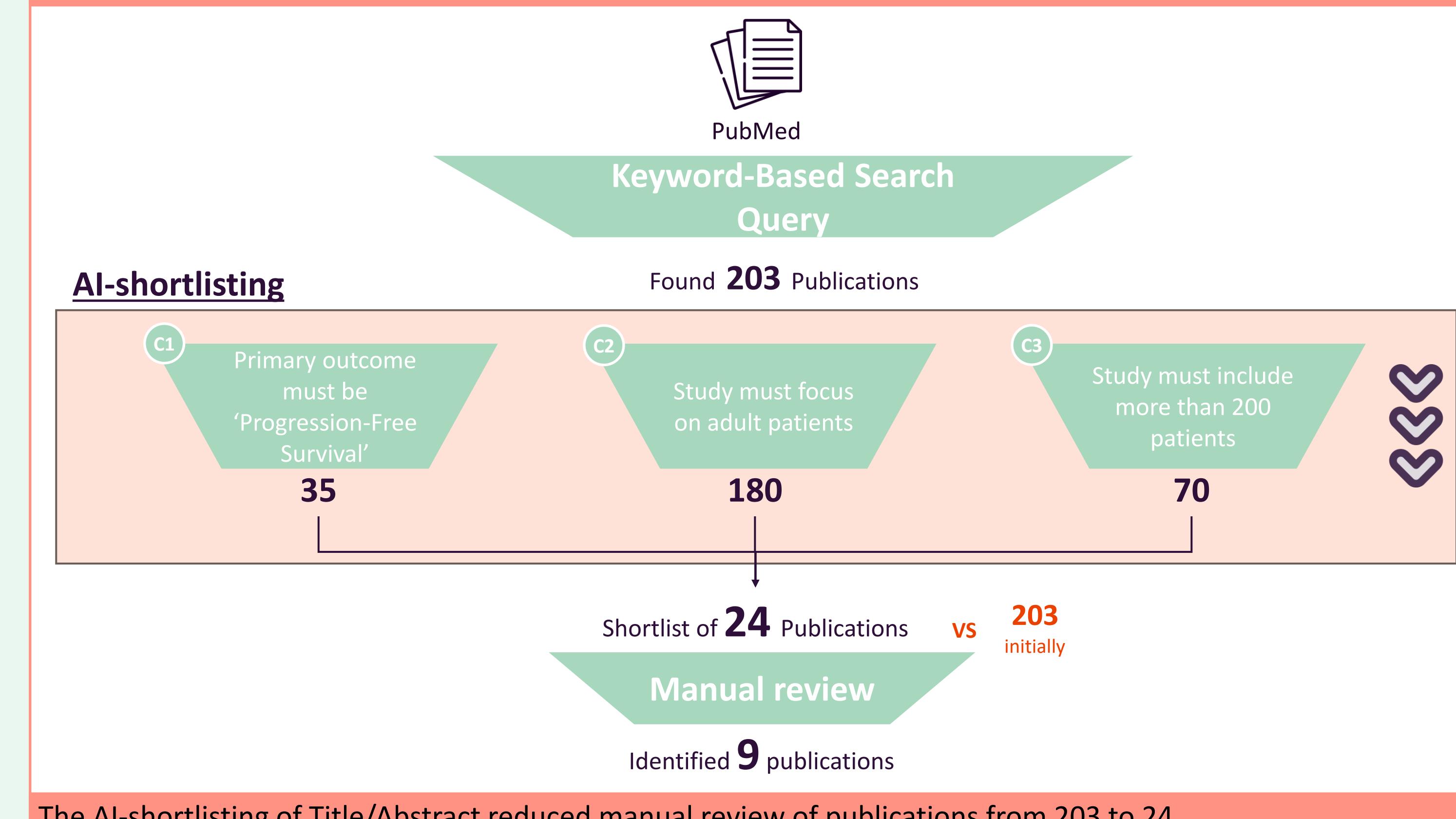
OBJECTIVE

This study aimed to develop and validate a semi-automated **AI-powered tool** to accelerate and enhance the SLR process by semi-automating **title/abstract screening**, enhancing **efficacy** and curtailing **time consumption**, while preserving methodological **rigor** and adherence to **established systematic review methodologies**.

METHODS

The AI assistance in the developed tool intervenes at the second step of the literature review process - the title/abstract screening based on **reviewer-defined YES/NO criteria** - following the initial keyword-based search. The reviewer then manually reviews the AI shortlisted publications.

Figure 1: Semi-automated Literature review using LLM to assess criteria given by reviewer



The **LLM prompting framework** is based on two steps:

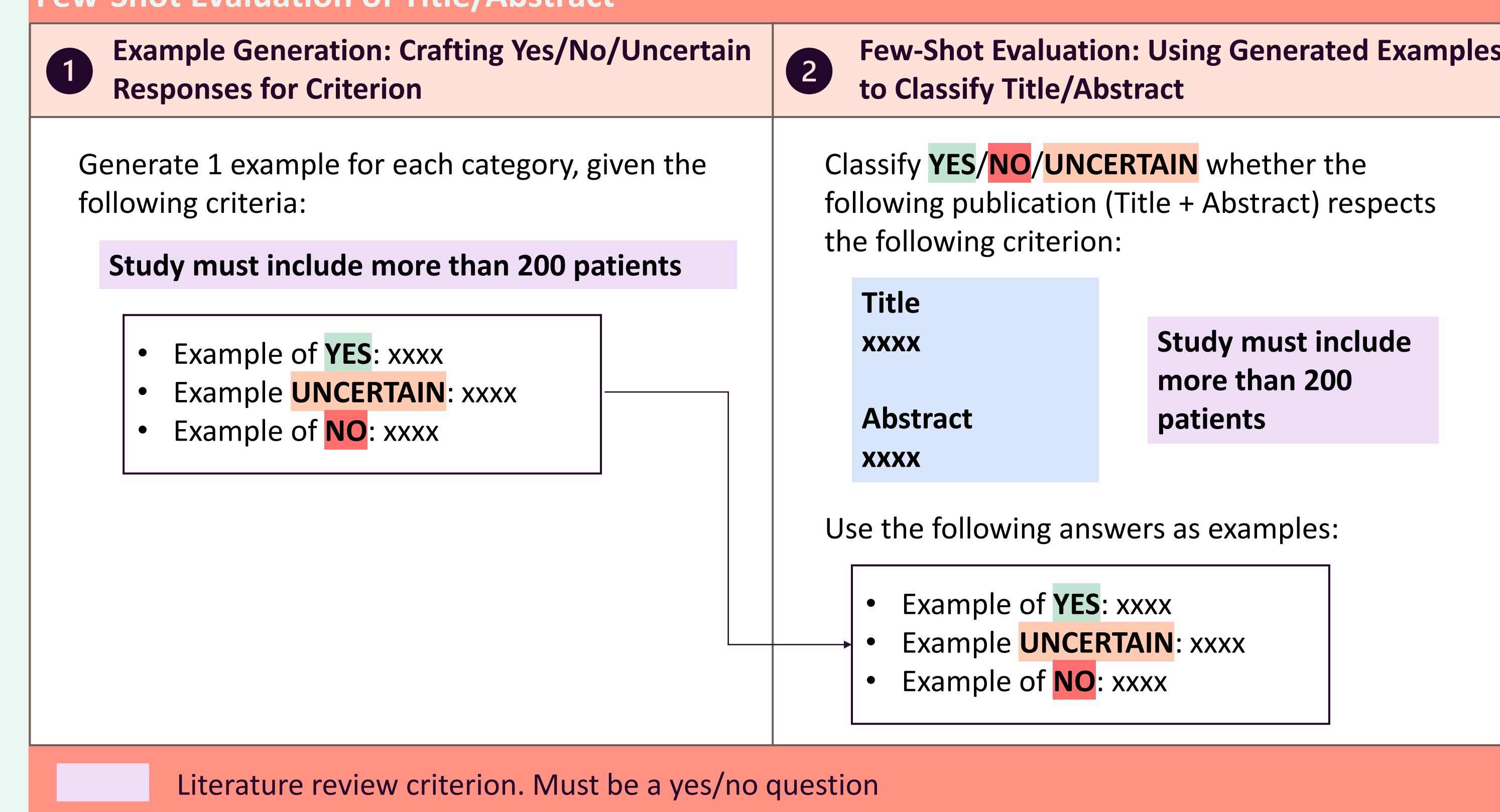
1. Uncertainty-aware prompting

Tackles hallucinations by forcing explicit triage: YES (meets criteria), NO (does not meet criteria), or **UNCERTAIN** (requires reviewer input). This ensures no false positives/negatives slip through unchecked.

2. Few-shot learning

Provide examples of YES/NO/UNCERTAIN answers to the LLM, to help it internalize criterion and prevent misaligned responses.

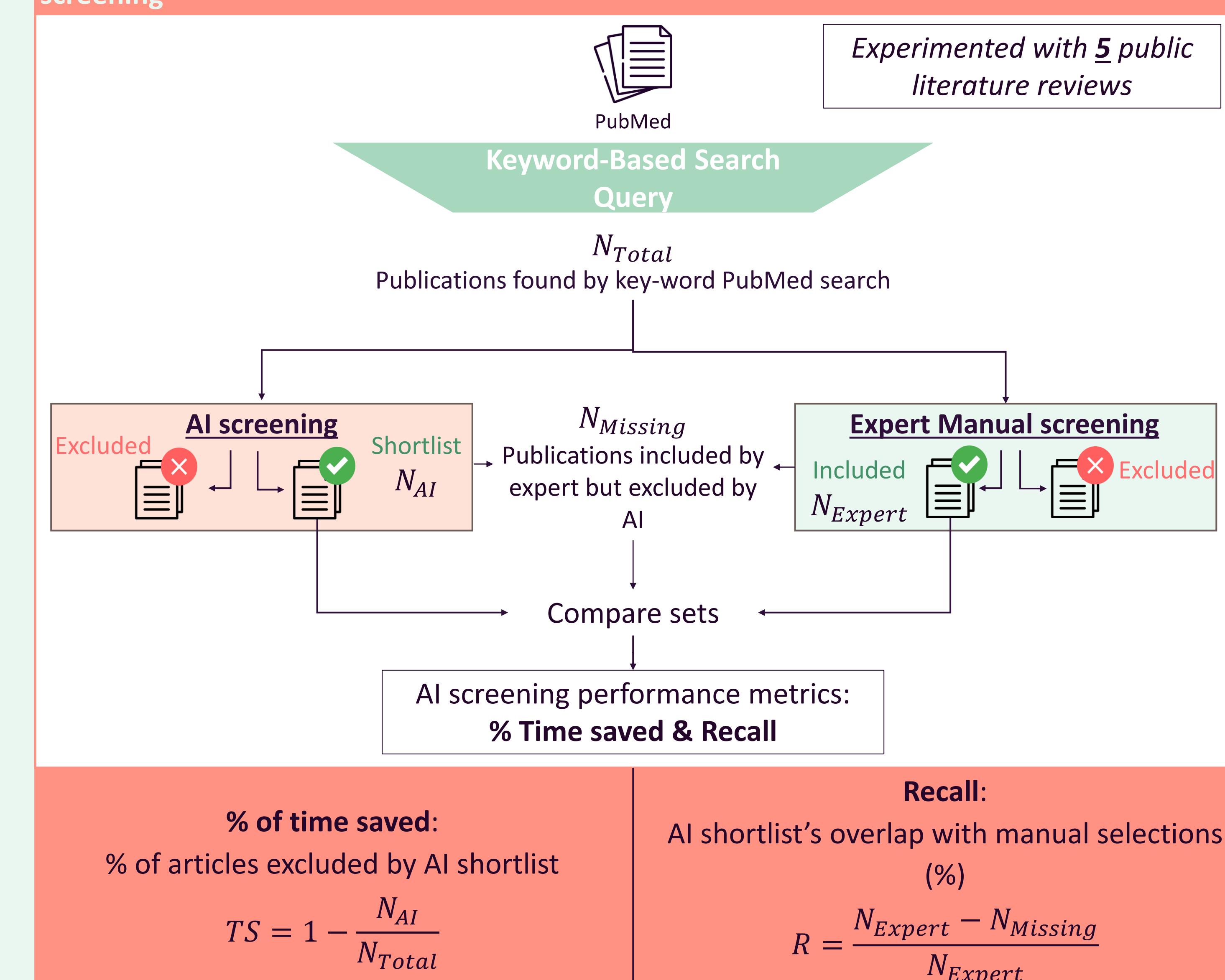
Figure 2: Two-Step Automated Classification of Criterion: From LLM-Generated Examples to Few-Shot Evaluation of Title/Abstract



Experiments to evaluate the tool

- To evaluate the performance of the tool in pre-selecting the right articles for the reviewers, we identified several published systematic reviews and tried to reproduce them.
- Using the public PubMed queries, the original sets of publications were retrieved. Then the sets of publications manually screened by experts were compared to the shortlist automatically screened by our AI-screening tool.
- Mistral-Large 2024** was the model used for all inferences.

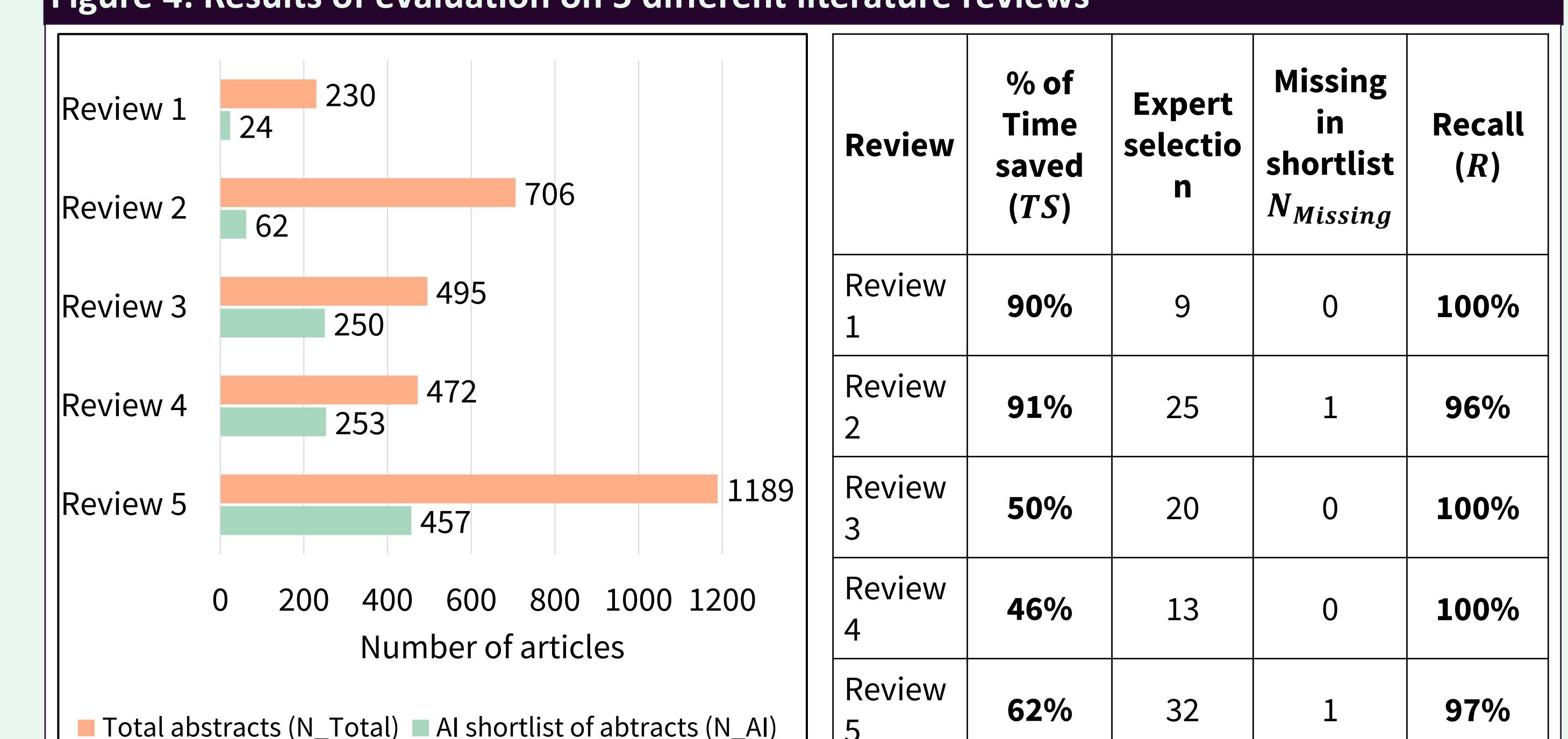
Figure 3: Process to evaluate the performance of the AI-Powered tool in Title/Abstract screening



RESULTS & DISCUSSION

- As shown in Figure 4, across the five replicated literature reviews used to test the semi-automated framework, the AI shortlists reduced the number of abstracts requiring manual screening by **46% to 91%**.
- Nearly all articles identified by human experts were included in the AI shortlists, with only two missed articles (reviews 2 and 5), corresponding to a **recall above 96%**.
- By designing a conservative prompting strategy, encouraging the model to answer "UNCERTAIN" when appropriate, a high recall was maintained while further decreasing the number of articles requiring manual assessment.

Figure 4: Results of evaluation on 5 different literature reviews



CONCLUSION

The AI-assisted shortlisting method reduced abstract screening effort by 46–91% (2–10x faster), while missing less than 5% of relevant studies, demonstrating both efficiency and methodological rigor.

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ABBREVIATIONS

AI, Artificial Intelligence; BM25, Best Matching 25; LLM, Large Language Model; NLP, Natural Language Processing; SLR, Systematic Literature Review

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CONFLICT OF INTEREST: NA

CONTACT INFO: Paul Loustalot, p.loustalot@quinten-health.com