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Title:

AI-Assisted Search Strategy Construction with Step-by-Step Instructions to Execute and Manage Searches Across Major Databases

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AI-Assisted Search Strategy Construction with Step-by-Step Instructions to Execute and Manage Searches Across Major Databases

Abstract

This manuscript introduces generative AI–assisted prompt template to help users translate their own keyword lists into database-ready search strategies. The workflow not only supports AI-assisted construction of syntactically correct search strategies but also provides step-by-step guidance for executing and managing these searches across major databases, including PubMed, Embase, Scopus, Web of Science, and the Cochrane Library. A small pilot test with three independent reviewers demonstrated that the workflow was usable and generated search strategies that ran without syntax errors. The complete two-part prompt and accompanying resources are openly available at https://github.com/ResearchCore/prompt2query.

Introduction

Systematic reviews and meta-analyses are foundational to evidence-based healthcare, enabling rigorous synthesis of research findings to inform policy and clinical practice.[1, 2] A critical first step in conducting a high-quality systematic review is an exhaustive and reproducible literature search aimed at retrieving as many relevant studies as possible.[3] The development of a comprehensive and reproducible search strategy tailored to multiple databases and citation indices, including PubMed, Embase, Scopus, Web of Science, and the Cochrane Library, has been emphasised as an essential part of Cochrane systematic reviews.[3, 4] Additionally, the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guideline requires the reporting of the search process, including the search strategy for at least one database, to enable readers to assess the scope and accuracy of the search, as well as replicate the process independently.[5] However, many researchers, especially those without formal training in information science, struggle to construct sensitive and reproducible search strategies due to the complexities of database-specific syntax and search logic.[6-8] For example, Salvador-Oliván et al. (2019) found, in their analysis of published systematic reviews that used PubMed in their literature searches, that many search strategy errors stemmed from a lack of understanding of information retrieval principles and the unique features of the PubMed interface.[9] This challenge is further compounded when users are unfamiliar with controlled vocabulary systems such as MeSH in PubMed or Emtree in Embase, or when they fail to correctly format field-specific searches across platforms. As a result, poorly designed search strategies often yield either overly narrow or excessively broad results, leading to biased evidence synthesis or missed studies.[10, 11]

Currently, suggested strategies advocated to improve the quality of search strategies primarily depend upon the inclusion of "information specialists", as has been recommended for Cochrane Reviews[3] and by the Institute of Medicine (US) Committee on Standards for Systematic Reviews of Comparative Effectiveness Research.[12] The inclusion of experts from library and information science backgrounds in the review team has been shown to boost the reproducibility and accuracy of searching in systematic reviews. [7, 13, 14] Alternatively, it has been suggested that search strategies be peer-reviewed in advance by librarians or information specialists using the PRESS checklist.[6] However, relying on the expertise of information specialists and librarians competent in formulating and conducting systematic literature searches is not always feasible for researchers in low-resource settings. It has been often stated in published research that, in developing countries, the capacity to conduct systematic reviews is constrained by a lack of trained personnel and limited access to resources.[15] Particularly, the scarcity of "search experts", such as information scientists and librarians, is glaring in low- and middle-income countries (LMICs).[16] Furthermore, even in those few LMIC institutions where information specialists or medical librarians are available, the financial implications of involving them can be prohibitive. A librarian's contribution to a systematic review demands time and expertise, translating into substantial personnel and infrastructure costs, which are often underestimated but can pose significant barriers for unfunded or minimally funded reviews, especially within LMIC institutions.[17] Therefore, there is a critical need for pragmatic, scalable alternatives that uphold the rigour of database-specific search strategies while remaining accessible to researchers in resource-constrained settings. This need is further underscored by the growing volume of systematic reviews originating from LMICs,[18] a trend reflecting increasing research activity and local policy relevance in these settings. Yet, without equitable access to information science expertise, many of these reviews risk suboptimal search quality, which can compromise the reliability of evidence synthesis and downstream policy decisions.

Artificial Intelligence (AI) and Large Language Models (LLMs) offer a potential solution to bridge this gap. The application of generative AI in systematic reviews has garnered increasing attention, particularly for tasks such as screening, summarisation, and data extraction.[19, 20] As noted in the Cochrane Handbook (2024), there is a burgeoning ecosystem of AI tools, including general-purpose LLMs like ChatGPT and Claude, as well as domain-specific tools like Consensus and SciSpace, being explored for their utility in systematic review workflows.[21] Systematic mapping of these tools has identified promising applications across multiple review stages,[22-24] yet the role of AI remains mainly concentrated on the "screening" and "extraction" stages,[19, 20] with its utilisation in search strategy design being notably underdeveloped.

There is significant potential for LLMs to assist non-specialist users in generating structured, reproducible, and database-specific search strategies. However, this potential can only be realised through carefully designed prompting frameworks and standardised templates that minimise user error and maximise reproducibility. Therefore, in this step-by-step tutorial manuscript, we aim to provide our readers a structured template to generate database-specific (PubMed, Embase, Web of Science, Scopus, and Cochrane Library) search strategies using syntax-free prompts. Through step-by-step instructions, this manuscript will guide users with limited knowledge of database searching to create a compiled list of keywords (involving thesaurus term identification (e.g., MeSH, Emtree) and the collection of relevant free-text synonyms) and embed it into an AI-assistance template. This template, through its initial detailed input section designed by human experts with previous knowledge of advanced database searching, instructs the LLM (ChatGPT in this case) to convert a simple list of keywords inputted by users in the second section of the template into a search-worthy query with Boolean logic and syntax incorporated. Thus, by leveraging the knowledge of advanced database searching of human experts, combined with the capability of LLM to follow detailed instructions faithfully, the AI-assistance template provided in this manuscript aims to enable users, particularly those without formal training in information retrieval, to construct robust search strings for their systematic reviews. An editable MS Word version of the complete two-part prompt is freely available at https://github.com/ResearchCore/prompt2query

Forming a search strategy alone is not sufficient for novice reviewers, particularly in settings where access to information specialists is limited. Even when a draft strategy is available, users often struggle with translating it into database-specific syntax, running it correctly, and managing the resulting search history. These practical steps are essential for achieving reproducible, well-documented searches, yet are rarely explained in a unified framework. To bridge this gap, the present workflow covers not only AI-assisted search strategy construction but also its accurate execution across major databases.

The flow of information in this Method section is organized into distinct sections. Section 1 describes the development of the AI-assistance template. Section 2 provides step-by-step instructions for compiling search keywords using both free-text and controlled vocabulary. Section 3 explains how these keywords are transformed into database-ready search strategies using ChatGPT through a structured two-part prompt. Section 4 outlines the procedures for running the generated strategies across databases, downloading results, removing duplicates, and preparing records for screening. Section 5 presents optional customizations and advanced search techniques that can expand or refine the basic strategies. Finally, Section 6 summarizes the small pilot test conducted with three independent reviewers to check usability and practical performance.

Methods:

1. Development of the Two-Part AI-assistance Prompt Template

The foundation of the AI-assisted framework developed in this manuscript is a structured, two-part prompt designed to guide ChatGPT in generating accurate, reproducible, and database-specific search strategies for systematic reviews. The purpose of separating instructions (Part 1) from content (Part 2) was to impose a high degree of control over the model's behavior, minimize hallucinations or formatting drift, and make the method user-friendly for non-specialists.

1.1. Part 1: Instruction Layer Built from Human Expertise

Part 1 (instruction layer built from human expertise) is a non-editable block of text that encodes detailed, database-specific guidance for how ChatGPT should construct the final search strategy using the terms provided in Part 2. This instruction layer was meticulously developed by the authors in consultation with experienced information specialists and by referring to publicly available syntax guides and documentation from MEDLINE (via PubMed), Embase (via Embase.com), Web of Science (via Clarivate), Scopus and Cochrane Library.

The Part 1 prompt includes specific rules on the use of Boolean operators (AND/OR), truncation (*), proper nesting with parentheses, database-specific field tags (e.g., [tiab] for PubMed, .ti,ab.kw for Embase, etc), placement and formatting of thesaurus terms (e.g., MeSH Terms in PubMed, Emtree in Embase). To ensure clarity and model compliance, the instruction set also includes formatting expectations such as separating each conceptual element (e.g., population, intervention, outcome) onto distinct lines, indenting Boolean blocks for readability, and suppressing explanations or notes in the output. The construction of Part 1 was additionally informed by prior scholarly and practical guidance on best practices in search strategy design,[3, 21] including pointers on Boolean and syntax rules[4, 25-27]. Part 2 was designed with simplicity and ease of use in mind, so that users will need only copy-paste their compiled list of keywords (free text-terms and thesaurus terms) in the respective sections.

This template intentionally excludes advanced search operators such as proximity commands, specialized wildcards, and database-specific adjacency functions. These features vary widely across platforms and often have different meanings or syntax, increasing the risk of incorrect or non-transferable results when generated through an AI model. By limiting the workflow to universally recognized Boolean structures and controlled vocabulary terms, we aimed to maximize cross-database reproducibility. Users needing advanced operator functionality should manually refine the generated strategies or consult an information specialist.

It is essential to clarify that the scope and purpose of this manuscript was not to assess ChatGPT's intrinsic knowledge of Boolean operators or database-specific syntax rules. Instead, we aimed to show that ChatGPT, when guided by a structured expert-defined prompt (Part 1), can reliably translate a user-supplied list of search terms (Part 2) into accurate and reproducible search strategies across different databases. In this context, the model functions as a compliant assistant executing a standardized protocol rather than as a source of syntactic expertise, encouraging human-AI collaboration rather than complete unguided automation.

2. **Preparing Part 2 of AI-assistance Prompt Template: Compiling Free-Text Terms and Thesaurus Terms**

The foundation of this method lies in identifying distinct 'elements' within a research question, commonly guided by frameworks such as PICO (Population, Intervention, Comparator, Outcome), and organizing them into modular search blocks. Each block comprises two components: (1) thesaurus terms, which are standardized subject headings assigned by databases (e.g., MeSH in PubMed, Emtree in Embase), and (2) free-text terms, which are natural language keywords searched within the title, abstract, and keyword fields. Users are required to provide these inputs for each 'element', which are then integrated using a generative AI prompt. The system generates fully formatted search strategies for five major databases: PubMed, Embase, Scopus, Web of Science, and the Cochrane Library, aiming to improve syntactic correctness and reproducibility given user-supplied terms without requiring prior expertise in database-specific search language. The following steps outline the process for compiling and structuring these terms before they are submitted to ChatGPT.

2.1. Identifying and Formatting Free-Text Terms Using Commas

The first step involves identifying relevant free-text terms for each element of the research question. These terms should include synonyms, singular and plural forms, American and British English variations, and common spelling differences (e.g., "tumor" vs. "tumour"). Apart from expert input, users are encouraged to examine keywords used in previously published systematic reviews on similar topics, refer to the list of synonyms provided by database thesauri (referred to as *Synonyms* in Emtree and *Entry Terms* in MeSH), consult online resources such as blocks.bmi-online.nl, and utilize tools such as ChatGPT and Google Search to explore lexical variations and generate a comprehensive set of free-text terms for each element. All selected terms should be arranged in a comma-separated format. Importantly, only those terms that demonstrate reasonable specificity and relevance to the research objective should be included to avoid the retrieval of irrelevant literature. Arrange the selected free-text terms for each specific element in a comma-separated format, such as: dengue, dengue fever, breakbone fever, break-bone fever.

Users can also use database-specific truncation, an asterisk (*), to capture different word endings while keeping the search manageable. Adding * after the root of a word (at least 4 characters in PubMed, and at least 3 in Web of Science) tells the database to retrieve all terms that start with that root. For example, serotype* retrieves serotype, serotypes, serotyped, and similar variants.

2.2. Identifying and Collecting Thesaurus Terms for PubMed and Embase

The second step involves retrieving thesaurus terms (also known as controlled vocabulary terms), which are standardised subject headings used for indexing articles in bibliographic databases. In PubMed, these are known as MeSH (Medical Subject Headings). To locate them, visit pubmed.gov, scroll down the homepage, and under the "Explore" section, click on "MeSH Database". In the MeSH Database interface, type a relevant keyword into the search bar and press Search. Select the most appropriate MeSH term from the list, and then click "Add to search builder" on the right-hand side. This generates a formatted term such as "Dengue"[Mesh], which can be copied and included in the search strategy. Repeat this process for each relevant element of your research question. Arrange all MeSH terms in a comma-separated format, ensuring correct syntax. Arrange the selected MeSH terms for each specific element in a comma-separated format, such as: "Disease Outbreaks"[Mesh], "Epidemics"[Mesh].

In Embase, the controlled vocabulary is referred to as Emtree. To access it, go to Embase through your institutional subscription. Click on the "Emtree" option (usually available on the top navigation bar), enter your keyword, and click Search. Once the correct Emtree term appears, click "Add to query builder" available on the right side of the screen, and the system will display the search syntax automatically, e.g., 'dengue'/exp to indicate term explosion. Copy this formatted term and paste it into the draft block. Repeat this process for all relevant elements. Organise the Emtree terms with correct syntax, separating them using commas. Arrange the selected Emtree terms for each specific element in a comma-separated format, such as: 'serotype'/exp, 'seroepidemiology'/exp.

2.3. Structuring Terms into Draft Search Blocks and Building a Draft Search Block Library

Once you have completed Step 1 (collecting free-text terms) and Step 2 (identifying thesaurus terms), the next step is to organise them into a structured Draft Search Block Library. This library provides a flexible and modular foundation for building search strategies that can be used in current and future systematic reviews. Each draft search block corresponds to one element of your research question (e.g., disease, population, exposure, outcome), and includes both thesaurus and free-text terms.

Each draft search block should begin with the element label, which is a concise descriptor of the element (such as "Dengue" or "Serotype"). The draft block then lists thesaurus terms drawn from major databases. These thesaurus terms are separated by a semicolon (;) to indicate database specificity within the same block. Next, free-text terms are added. [Table 1]

Table 1: Draft Search blocks library (Draft search blocks are illustrative and provided for explanatory purposes; they are not finalized or fully optimized strategies)

Element	Draft Search block
Dengue	Element: Dengue Thesaurus terms: PubMed: "Dengue"[Mesh]; Embase: 'dengue'/exp Free terms: dengue, dengue fever, Breakbone Fever, Break-Bone Fever

Outbreak	Element: Outbreak Thesaurus terms: PubMed: "Disease Outbreaks"[Mesh], "Epidemics"[Mesh]; Embase: 'epidemic'/exp Free terms: outbreak*, upsurge, epidemic
Serotype	Element: Serotype Thesaurus terms: PubMed: "Serogroup"[Mesh]; Embase: 'serotype'/exp, 'seroepidemiology'/exp Free terms: Serogroups, Serotype*, Serovar*

2.4. Copying and Pasting Draft Search Blocks from the Library into the Prompt

To transfer relevant draft search blocks from the draft search block library into the search strategy builder prompt, begin by selecting the desired cells from your Word table. Once all relevant cells are selected, copy them. You can then paste the copied content into Part 2 (next section) of the AI prompt, replacing the placeholder text.

3. Generating the Search Strategy Using ChatGPT

3.1. Using the AI-assistance Prompt Template: Part 1 (Fixed Instructions) and Part 2 (User Input)

The next step is to use a pre-structured ChatGPT prompt designed to automatically generate a comprehensive, database-specific search strategy for systematic reviews. This prompt is divided into two parts. In Part 1, ChatGPT is provided with detailed instructions on how to construct the search strategy, including formatting rules, Boolean logic, field codes, truncation, and quotation conventions specific to each database, such as PubMed, Embase, Scopus, Web of Science, and the Cochrane Library. The user is expected to make no changes in Part 1 for optimal results (See Box 1).

To complete Part 2 of the prompt, the user should begin by entering the title of their systematic review to provide context for the search strategy. Next, for each element of the review question (e.g., *Dengue*, *Outbreak*, *Serotype*), include a clearly labelled line starting with “Element:” followed by the element name. Below each element, add the corresponding thesaurus terms, prefixed with “Thesaurus terms:” and formatted using database-specific syntax, such as "Dengue"[Mesh] for PubMed and 'dengue'/exp for Embase, separated by a semicolon (;). Then, add the free-text terms on a new line, beginning with “Free terms:” and listing the terms separated by commas, not using Boolean operators like OR. The free-text terms should include spelling variations, synonyms, and truncation (using *) where applicable.

3.2. Submitting the Prompt and Retrieving the Output

Once both parts of the prompt are prepared, copy and paste the entire text (Part 1 followed by Part 2) into a new session in ChatGPT. If the output appears in a visual format (such as a scrollable canvas), instruct the model to regenerate as plain text by typing, "Please regenerate this output as plain text without formatting or canvas."

Copy text using the 'copy text' button and paste it into the Word document. If this causes a formatting error, manually scroll to highlight the text, copy it, and then paste it into the Word document. The output will typically include a title, separate strategy blocks for each database, and structured tables with placeholders for dates and the number of results. In Word document, if the tables appear without borders, select them one by one and format using Home > Paragraph > Borders > All Borders in Microsoft Word.

Box 1: Full Search Strategy Prompt for Generating Syntax-Specific Queries Across All Databases (Also available as an MS Word file in the Supplementary Materials)

Part 1: Defining the Approach

You are an experienced information specialist with expertise in systematic reviews, skilled in designing highly sensitive and specific search strategies tailored to research questions across major databases. Authors frequently approach you to develop search strategies for their systematic reviews, relying on your ability to translate complex research questions into comprehensive, structured, and reproducible search strategies.

Authors will deconstruct the research question into distinct conceptual elements to facilitate the development of a structured search strategy. For instance, consider the Cochrane review titled "Factors that influence caregivers' and adolescents' views and practices regarding human papillomavirus (HPV) vaccination for adolescents: a qualitative evidence synthesis." The research question underlying this review can be broken down into the following key components for the purpose of search strategy development: Papillomavirus, Vaccine, Adolescent, and Qualitative Research. However, the way elements are defined may vary among authors, depending on the level of sensitivity and specificity they aim to achieve in their search strategy.

For each element, Authors will separately provide you with thesaurus terms and free-text terms. You will create a separate search block that includes both thesaurus terms and free-text terms. In each search block, list thesaurus terms with their corresponding field codes and free-text terms with the appropriate field codes for each database, ensuring that each term is separated by the Boolean operator ‘OR’. Do not change field codes for thesaurus terms.

For Free-Text Terms:

Ensure that all free-text terms are enclosed in double quotation marks (" ") when searching in PubMed, Scopus, and Web of Science. If the quotation marks are missing, add them—for example, vitamin d should be written as "vitamin d". In Embase, replace double quotation marks with single quotation marks (' ') for all free-text terms, and add them if they are missing—for example, vitamin d should be written as 'vitamin d'. In the Cochrane Library, double quotation marks do not work correctly for multiword keywords. Instead, use the NEXT operator inside parentheses—for example, "child health" should be written as (child NEXT health). Single-word keywords can be used without quotation marks in Cochrane. If an asterisk (*) is used at the end of a free-text term to indicate truncation, retain it exactly as provided without any modification.

For Thesaurus Terms:

Use author provided database-specific field codes with thesaurus terms for each database. In PubMed, Medical Subject Headings are indicated using the [MeSH] tag. In Embase, thesaurus terms are denoted with '/exp' to capture exploded terms. Additionally, some search terms may not be part of a database's controlled vocabulary (thesaurus), but the author may specify using field codes in certain databases. These terms should be included under the thesaurus section and formatted with the appropriate field codes as provided in the prompt.

Author will provide free-text terms that are common across all databases. In PubMed, free-text terms should be searched using the [tiab] field to capture occurrences in the title and abstract. In Embase, apply the ():ti,ab,kw format to search within titles, abstracts, and keywords. For Web of Science, use TS= to conduct topic searches. In Scopus, implement TITLE-ABS-KEY() to locate terms within titles, abstracts, and keywords. By default, search in the title, abstract, and keywords fields. In the Cochrane Library, use the ():ti,ab,kw format to search free-text terms within the title, abstract, and keyword fields. It is essential that you do not add any additional keywords—strictly use only the terms that the author will provide.

Example Search Strategy for One Element- You will arrange thesaurus terms and free text terms using Boolean operator -OR, in following way:

PubMed:

"Papillomaviridae"[Mesh] OR "Papillomavirus Infections"[MeSH] OR "hpv"[tiab] OR "papillomavirus*"[tiab] OR "papilloma*"[tiab] OR "papilloma virus*"[tiab]

Embase:

'Papillomaviridae'/exp OR 'papillomavirus infection'/exp OR ('hpv' OR 'papillomavirus*' OR 'papilloma*' OR 'papilloma virus*'):ti,ab,kw

Web of Science:

TS=("hpv" OR "papillomavirus*" OR "papilloma*" OR "papilloma virus*")

Scopus:

TITLE-ABS-KEY ("hpv" OR "papillomavirus*" OR "papilloma*" OR "papilloma virus*")

Cochrane:

(hpv OR papillomavirus* OR papilloma* OR (papilloma NEXT virus*)):ti,ab,kw

Having completed the training, you can now proceed with the following instructions.

Using the input provided in Part 2, create a separate search block for each element and develop structured search strategies for PubMed, Embase, Web of Science, Scopus, and Cochrane. In Part 2, author will supply element-specific thesaurus terms and free keywords for the review in the following order: Element1, Thesaurus1, Free term1, Element2, Thesaurus2, Free term2, and Element3, Thesaurus3, Free term3.

Author needs your response in this output Format:

Title: (Put title of the systematic review here once in the start of document)

(following is example for PubMed, repeat this for all databases)

Database Name: PubMed (you need to mention database name here)

Date of Search: (Just print this heading. Leave a blank space after it)

Number of results: (Just print this heading. Leave a blank space after it)

(Here make a table with following details)

Column 1 (Elements), Column 2 (Search Block), Column 3(Search no.), Column 4 (Results No.)

Element 1 name, Block 1, #1,

Element 2 name, Block 2, #2,

Element 3 name, Block 3, #3,

Combined, #1 AND #2 AND #3, #4,

Repeat this format for each database.

Part 2: Preparing the Inputs

Title: Epidemiological Patterns of Dengue Outbreaks in Relation to Serotype Circulation: A Systematic Review.

Element: Dengue
Thesaurus terms: PubMed: "Dengue"[Mesh]; Embase: 'dengue'/exp
Free terms: dengue, dengue fever, Breakbone Fever, Break-Bone Fever

Element: outbreak
Thesaurus terms: PubMed: "Disease Outbreaks"[Mesh], "Epidemics"[Mesh]; Embase: 'epidemic'/exp
Free terms: outbreak*, upsurge, epidemic

Element: serotype
Thesaurus terms: PubMed: "Serogroup"[Mesh]; Embase: 'serotype'/exp, 'seroepidemiology'/exp
Free terms: Serogroups, Serotype*, Serovar*

3.3. Output Formats and Troubleshooting

During testing, no hallucinated terms, fictitious syntax, or incorrect Boolean formatting were observed across any of the strategies generated using the template. ChatGPT consistently adhered to the fixed instructions provided in Part 1. However, we caution users that LLMs may exhibit variability across sessions or versions and recommend careful review of outputs, especially when applying the template to unfamiliar databases or concepts. If any such issues are encountered, the affected portion of the prompt can be regenerated by asking ChatGPT to revise only that database block, while reapplying the Part 1 rules.

4. Running the Strategy in Databases and Preparing for Screening

Once the AI-generated search strategy is ready, the next step is to run it on each targeted database. For consistency and reproducibility, follow a block-by-block approach for all databases. After running the searches, export the final combined results in file format with the

".ris" extension (or ".nbib" for PubMed), which can be used for citation management and screening.

4.1. Running the Strategy in PubMed

To run a block-by-block search in PubMed (https://pubmed.ncbi.nlm.nih.gov/), go to the 'Advanced' Search page by clicking the Advanced button located just below the search box on the homepage. In the PubMed Advanced Search Builder section, paste your first search block (e.g., *Dengue*) into the Query box, then click "Add to History", which appears when you click the downward arrow next to the search button. Repeat this process for your second and third search blocks (e.g., *Outbreak* and *Serotype*), clicking "Add to History" after entering each block. Once all blocks have been added, use the builder to combine them using the AND operator (e.g., #1 AND #2 AND #3), and click "Add to History" again. Record the number of search results displayed in the Results column for each block and the final combined query in your search log file. Clicking on the result numbers (in blue) will take you to the corresponding results page. To export the final search results, click "Send to" at the top of the results page, choose "Citation Manager", select 'All results' from the dropdown menu, and click "Create File" to download the results in ".nbib" format.

4.2. Running the Strategy in Embase

To conduct a block-by-block search in Embase (accessed through https://www.embase.com/), begin by clicking the 'Advanced' option on the homepage to access the Advanced Search section. Once there, uncheck all default filters, limits, or field restrictions to ensure a clean and unrestricted search environment. Paste your first search block into the search box and click Search. This will direct you to the search results page. From there, paste and run your second and third search blocks one at a time in the same search box. Each executed search will appear as a separate line (e.g., #1, #2, #3) in the Search History, displayed above the results. After entering and running all search blocks, select the checkboxes next to the relevant queries in the Search History. Then click 'Combine with AND', located just above the list of search queries. This action will generate a new combined search string. To export the final results, click the checkbox next to the combined search string (located near the 'Results' heading). Open the 'Select number of items' dropdown and choose a range that includes all results, or specify a custom range depending on Embase's export limits. Then, click Export from the results bar (not the history bar), select the RIS format, and download the ".ris" file.

4.3. Running the Strategy in Web of Science

On the Web of Science homepage (https://www.webofscience.com/), click the 'Advanced Search' option to open the Advanced Search Query Builder. In the 'Query Preview' box, paste your first search block along with Web of Science syntax, then click 'Add to History'. Repeat this process for your second and third search blocks, ensuring each block is added individually to the Search History. Once all search blocks have been added, scroll to the bottom of the page where the search queries appear in the Search History. Check the boxes next to the relevant search lines (e.g., #1, #2, #3), then click 'Combine Sets' and choose the AND operator to merge them. A new combined set (e.g., #4) will be created. Make a note of the number of results for each individual block and the combined set in your search log file. To export the results, click on the number of results corresponding to the combined set to view the records. Then, click the 'Export' button located above the results list, choose the ".ris" format, and proceed. A pop-up window titled 'Export Results to RIS' will appear to complete the export process. Web of Science permits exporting up to 1000 records per batch. If your total results are fewer than 1000, simply select the full range (e.g., 1 to [number of results]) and export. If the total exceeds 1000, export in multiple batches. Start with the range 1–1000, export the file, then adjust the range to 1001–2000, and repeat. Continue this process until all results have been successfully downloaded.

4.4. Running the Strategy in Scopus

To perform a block-by-block search in Scopus, begin by clicking on the 'Advanced Document Search' option available on the homepage (https://www.scopus.com/pages/home). This will open the advanced search interface where you can manually enter and execute each search block. In the 'Enter query string' search box, paste your first search block and click Search. This will display the results for that block. To run the next block, click 'Edit in advanced search' at the top of the results page. Replace the query with your second search block, and click Search again. Repeat this process for all remaining search blocks. Once all individual search blocks have been searched, navigate to the 'Search' tab at the top of the page. Your complete search history will be visible just below the search bar. Here, check the boxes next to the individual searches (e.g., #1, #2, #3) that you want to combine. Click 'Combine Queries', select the 'AND' operator, and then click 'Show Results' to display the final combined search output. To export the results, click on 'Export' at the top of the results page. In the Export dialogue box, select RIS format, choose All fields, and then click Export to download the ".ris" file. Finally, return to the Search page to record the number of results retrieved for each individual search block.

4.5. Running the Strategy in Cochrane Library

To conduct a block-by-block search in the Cochrane Library (https://www.cochranelibrary.com/), start by clicking on the 'Advanced Search' option located just below the search bar in the upper-right corner of the homepage. Then, open the 'Search Manager' tab to begin building your search. Paste your first search block into the input field and click 'Continue'. Repeat this process for your second and third search blocks. Each query will appear as a separate line in the search history (e.g., #1, #2, #3). To combine the blocks, enter a new line such as #4 = #1 AND #2 AND #3 and press Enter or click the search icon. The combined results will appear below. Click the result count in the blue box to view the records. Be sure to note the number of search results for each individual block and the combined query for documentation purposes. To export the results, go to the 'Systematic Reviews (SR)' tab. Click 'Select All', then choose 'Export Selected Citation', select the RIS format, and download the file. Repeat the same steps under the 'Trials' tab to export records of clinical trials.

4.6. Managing Search Results: Renaming, De-duplication and Start of Screening

After completing searches across multiple databases, all downloaded ".ris" and ".nbib" files should be renamed using a standardised naming convention. Each filename should include the database name, the number of retrieved records, and the date of the search. If a database requires multiple exports due to download limits (e.g., Web of Science), add a sequential batch number (e.g., _1, _2) to distinguish between files. This naming system ensures clarity and traceability during the review process. In the PRISMA flow diagram, [28] the number of results obtained from each database should be documented under the "Identification" section.

Deduplication can be done using any reference manager. To remove duplicates using Zotero (an open-access reference manager available at https://www.zotero.org/), import all renamed citation files into a single collection. Once imported, select the "Duplicate Items" folder in the left sidebar. Zotero automatically detects potential duplicates based on key metadata fields such as title, author, and publication year. Review each group of duplicates displayed in the centre pane. Zotero highlights the most complete entry as the default. You may manually edit fields if needed. Then, click "Merge Items" to consolidate them into one record. Repeat this for all identified duplicate sets until your library contains only unique references.

To remove duplicates in EndNote, most users can rely on the default "Find Duplicates" function, which compares key fields such as author, year, and title. This simple approach works well for smaller projects and for users who do not need highly detailed de-duplication. For more advanced users, especially those working with large search sets in systematic reviews, the Bramer method provides a more rigorous option.[29] It reduces manual workload and improves accuracy compared with doing duplicate checks in a single pass.

After de-duplication is complete, select the final set of references and export them as an RIS (.ris) file using the export option in your reference manager to save the exported file locally. This cleaned and standardized '.ris' file is now ready for screening. To proceed, log in to the chosen screening platform, such as Covidence (subscription-based) or Rayyan (free with optional premium features: https://www.rayyan.ai/). Create a new review, navigate to the Add References section, and upload the RIS file. The platform will then process the entries, allowing efficient blinded screening of titles and abstracts.

5. Customization and Advanced Syntax Handling

This AI-based prompt is designed to generate structured search strategies using predefined rules and field codes. However, it is not recommended for use with the 'NOT' Boolean operator, as this can unintentionally exclude relevant studies and is difficult to standardise across databases. Additionally, if a user wishes to apply a different syntax or field code to a specific free-text term, for example, restricting it to the title only or using database-specific filters, this should be done by manually adding the free-text term under the "Thesaurus terms" section of the relevant search block, with the appropriate field code. This workaround allows for greater control and precision. This method is also compatible with Scopus and Web of Science, where advanced users may want to apply unique syntax or filters. In such cases, users must explicitly label the database name (e.g., Scopus or Web of Science) within the Thesaurus terms section of the search block, and include the full term along with its intended syntax.

While the rules of truncation (using an asterisk at the right-hand end of the root word) are largely similar across databases—though left-hand truncation is permitted in some, such as Web of Science—the use of within-word wildcards like "#", "?", or "$" to replace zero or one character varies between platforms. This feature is unavailable in PubMed, whereas in Ovid-based platforms such as Medline and PsycINFO, "#" substitutes exactly one unknown character and "?" can substitute for zero or one character. In Web of Science, "?" substitutes a single character, while "$" substitutes zero or one character. The rules become even more confusing in the case of Embase, where the syntax differs depending on the service provider. For example, in Embase.com the "?" represents a single character, whereas in Embase on Ovid SP it denotes zero or one character; similarly, the "$" symbol in Embase.com allows for zero or one character, while in Ovid SP it represents any number of characters.[26]

Users are advised to review the database-specific search rules before using these advanced techniques, or to seek help from an information specialist when possible. Additionally, reviewing the common errors in search strategies identified by Salvador-Oliván et al. (2019) and search tips based on Boolean and other syntactic rules documented by can provide a more informed perspective when using advanced searching options.[9]

6. Pilot Testing with Independent Reviewers

In this small pilot test involving three independent reviewers, all participants were able to format the raw search terms according to the Part-2 structure and use the two-part prompt to generate database-ready search strategies. The AI-generated strategies ran successfully in all major databases without syntax errors, and no hallucinated or missing terms were observed. The issues we encountered in PubMed were linked to errors in how Part-2 was formatted rather than any problem with the prompt itself: one keyword produced no results, and the wildcard was applied incorrectly. PubMed requires at least four characters before a wildcard, but we had placed it after only three. Reviewers also reported that the workflow was easy to follow and helped them run searches despite limited experience with Boolean operators and database syntax. Full methods and detailed results are provided in the Supplementary File.

Discussion

This article presents a novel, user-friendly method for constructing database-specific search strategies using generative AI and structured search blocks. By simplifying the process through syntax-free prompts and modular search blocks, the approach addresses a key barrier faced by researchers, particularly those who lack training in advanced database querying, including non-librarians. The integration of both thesaurus terms and carefully selected free-text terms ensures that the resulting strategies are both sensitive and reproducible, aligning with best practices outlined in the Cochrane Handbook and PRISMA guidelines.[3]

Our manuscript aims to aid in the automation of the search strategy development process, which continues the long legacy of utilising automation in systematic reviews. Over time, research has intensified to automate and subsequently expedite the multitude of individual steps involved in conducting systematic reviews, so that the publication of synthesised evidence can become more sustainable and keep pace with the rapidly changing evidence.[30] This rising interest in systematic review automation is easily understandable, considering the time investment required to conduct a systematic review, which has been estimated to be around 1139 hours (almost six weeks) of highly skilled manual work for a meta-analysis[31] while the total time from protocol registration to review publication has been seen to need more than 67 weeks on average[32]. Furthermore, due to the rapidly evolving field of evidence, new studies may become available during the lengthy review process, potentially making the completed review outdated by the time it is released.[33] Consequently, the development and availability for end-user utility of software tools, artificial intelligence (AI), natural language processing (NLP) and machine learning (ML) models, meant to decrease manual workload in systematic reviews, is rapidly growing.[34, 35]

The pilot testing showed that the two-part AI-assisted prompt framework was easy to use and worked well for reviewers who did not have advanced knowledge of Boolean operators or database syntax. All three testers were able to follow the instructions, format the terms correctly, and run the search strategies without major problems. These results suggest that the framework can be helpful for semi-experienced reviewers, especially in settings where expert support is limited.

However, this was a small pilot exercise, and more advanced testing is needed. Future evaluations should include a larger number of users with different levels of experience, testing across more topics and databases, and formal comparison with expert-developed strategies. This will help determine how well the method performs in different situations and how it can be improved further. Despite these limitations, the pilot provided encouraging evidence that the approach is practical and user-friendly.

Taking cognisance of this growing use of automation, the leading authorities in the field of evidence synthesis, namely Cochrane, the Campbell Collaboration, JBI and the Collaboration for Environmental Evidence (CEE), have united to formulate the joint AI Methods Group, aiming to define best practice guidelines for the appropriate use of AI in systematic review.[36] This methods group, along with individual experts from other prestigious organisations around the world, have now developed recommendations for Responsible AI use in Evidence Synthesis (RAISE), available open access for use by researchers on the open science framework (OSF).[37] This is part of the larger international efforts ongoing since 2015 under the umbrella of International Collaboration for the Automation of Systematic Reviews (ICASR), which brings together stakeholders from diverse academic backgrounds to brainstorm and collate automation tools for use by the global systematic reviewer community.[38-40]

Despite the widespread interest and increasing acceptance of AI use in other steps of systematic reviews, the same is lagging in systematic searching, which forms the core of systematic evidence synthesis. Tóth et al. (2024) in their scoping review of AI use in biomedical systematic reviews, reported that only 15.4% of their included articles dealt with automation in search as compared to the vast majority of publications (87.8%) focused on record screening and extraction.[41] Nevertheless, formulating a search strategy often demands a significant time commitment, with previous research stating that even expert information specialists require a mean duration of almost 27 hours to finalise the plan for a single systematic review.[42] Naturally, in comparison, untrained researchers or those with lower overall experience would need to invest many more manhours to complete the search strategy development stage.[43] This underscores the need for further research to advance automation for the searching process of systematic reviews.

Automation in the search process can be grouped into categories depending upon the sub-components of the search process itself, i.e., tools meant for identification and compilation of keywords and those meant to convert the list of keywords into a search strategy following Boolean logic and database-specific syntax, as well as translation of search queries from one database to another. Most of the published research on search automation has focused on the first category, i.e., keyword identification and compilation, especially using text mining approaches. Of late, the use of text mining tools (TMTs) is becoming increasingly common to retrieve keywords.[44] Tools such as AntConc, PubReMiner, MeSH on Demand, and Yale MeSH Analyzer aid the user in exploring and identifying potentially relevant keywords or controlled vocabulary terms (e.g., MeSH) by analyzing text corpora or PubMed records.[45] In another common text mining approach, relevant citations from a systematic review in the field are retrieved, in a section of these citations, "development set", TMTs are run to identify keywords from the titles and abstracts, and validation of the consequent search strategy is done in the remaining portion of citations, "comparator set". The best practice guidance in this aspect has been documented and adopted by Germany's Institut für Qualität und Wirtschaftlichkeit im Gesundheitswesen (i.e., Institute for Quality and Efficiency in Health Care - IQWiG).[25, 46, 47] Grames et al. (2019) and Kwabena et al. (2023) have reported using novel automated methods using keyword co-occurrence networks and NLP (R-based approach implemented in litsearchr and the Python-based tool Ananse, respectively) to identify and compile a deduplicated list of relevant keywords.[48, 49]

Considering the challenges in building a Boolean search query,[26, 27] automation is also being investigated to aid in the conversion of Boolean search strategies and syntax formatting across database platforms by using tools such as the Polyglot Search Translator, MEDLINE Transpose, and Macros in MS Word. [29, 50-52] However, highly sparse research exists to support the query-building process at the initial stage. Although reviews exist that summarize the process or identify common pitfalls,[4, 10, 26, 53] a step-by-step tutorial to guide the readers in their query-building exercise is not common. Alternative efforts to overcome challenges in Boolean query building have included visual and interactive approaches such as tile-based layouts, radial canvases, and conceptual mapping tools. [54-57] Building on these, Russell-Rose and Shokraneh (2019) developed 2Dsearch, a visual interface that lets users construct and refine search queries using a drag-and-drop canvas with automatic syntax handling and integration with tools like the Polyglot Search Translator.[27, 58] While 2Dsearch improves transparency and reduces syntactic errors, it lacks step-by-step guided walkthroughs or pre-built templates, and may still be difficult for novice users unfamiliar with structured searching or Boolean logic.

Another approach to simplifying Boolean search construction is the use of syntax-generating spreadsheet tools such as the Excel-based macro-enabled Search Builder 1.0, developed by Kamdar et al. (2015).[59] This tool allows users to input search terms categorized by PICO components and automatically generates search strings for PubMed and Embase, complete with Boolean operators and field tags. However, there is no option for the user to work with other databases. Another alternative that is, recently, being explored is the use of ChatGPT to automate query generation for systematic reviews, but the results have been mixed. Alaniz et al. (2023) and Wang et al. (2023) found that ChatGPT-generated queries often included irrelevant terms or misinterpreted logical structures, while Guimarães et al. (2024) showed that the tool failed to incorporate clinical jargon, entry terms, or appropriate filters for study types.[60-62] A standard limitation across these studies was the conflation of keyword identification with query formulation; many prompts expected ChatGPT to do both simultaneously, often without clearly separated steps or database-specific instructions. A more effective workflow could involve separating these tasks; first, using established automation tools to generate a robust list of keywords, and then employing a guided AI-assisted template, like the one proposed in our manuscript, to convert these into Boolean-ready search strings tailored to individual databases. Existing ChatGPT evaluations have not yet incorporated such structured prompting or modular handholding, nor do they offer step-by-step walkthroughs or prebuilt templates. [60-62] Thus, our manuscript helps overcome this usability barrier for novice users unfamiliar with Boolean logic or database syntax by encouraging human-AI collaboration rather than complete unguided automation.

Nevertheless, several concerns could have limited the interest of researchers in exploring AI-generated search strategies. LLMs trained on literature containing flawed search methods can yield biased results.[63] The outdated cut-off dates and limited transparency around the internal workings of the model and the nature of the training content of the LLMs have restricted academic trust in LLM-generated searches. [60, 62] Empirical assessments have flagged other issues such as hallucinated or inaccurate content, incorrect use of synonyms and controlled vocabularies like MeSH or Emtree, and errors in search syntax. [60-62, 64, 65] However, newer iterations, such as ChatGPT-4 and 5 trained on academic corpora, have been shown to have lower rates of hallucinated or inaccurate content compared to older versions such as GPT-3.5.[66] Despite these improvements, current AI tools are largely limited to exploratory use rather than structured search construction, and their outputs can vary depending on the quality of the input prompt, which in turn depends greatly on the user's expertise.[62]

The precision and recall of the final search strategy developed using the AI-assistance template detailed in our manuscript are, to a large extent, dependent on the quality of keywords compiled by the user. When compared to relying solely on expert input, the use of additional techniques to identify relevant keywords, such as reviewing the search strategies of published systematic reviews and text mining tools, can yield a more comprehensive list of keywords.[46, 47] While we have touched upon a few of the most important best practices in compiling a comprehensive search query, a detailed instruction on the same was out of scope for this manuscript. Hence, we advise our readers to refer to previously documented best practice guidelines (including the Cochrane Handbook) that expound on how to compile an exhaustive list of keywords and formulate a systematic search strategy.[3, 21] Additionally, useful resources can be found in previously published books, reviews and tutorial articles detailing the dos and don’ts of search strategy generation.[47, 65] For example, Bramer et al. (2018) present a step-by-step overview of the process of designing comprehensive and database-translatable search strategies for systematic reviews.[29] DeMars and Perruso (2022) highlight the benefits of combining free text-terms with controlled vocabulary or thesaurus terms to increase precision and recall of the search strategy.[67] Another publication proposes and evaluates automated methods of generating relevant MeSH terms from an initial Boolean query composed solely of free-text terms. [68]

Limitations and Future Work

The AI-assisted prompt framework offers a structured and reproducible way to build search strategies, but it has some limitations. Users who need advanced functions such as proximity operators or specialized wildcards may still need to refine the AI-generated strategies or seek help from an information specialist. The method is meant to support teams without access to expert searchers, not to replace professional input, and final strategies should be reviewed whenever possible. Output quality also depends on the LLM version, and results may vary across models or sessions. Larger studies with more users, different topics, and cross-database comparisons are needed to fully test robustness and reproducibility. In the future, user-friendly tools such as browser extensions or web forms could further improve accessibility for novice reviewers.

Conclusion

In conclusion, this guide offers a practical and scalable solution for generating high-quality, reproducible search strategies using generative AI. By separating the development of search blocks from the complexities of database-specific syntax, it empowers researchers with limited search expertise to build robust strategies across major bibliographic databases. The modular design of the search block library, combined with AI automation, ensures both consistency and customisation. As systematic reviews continue to grow in volume and importance, tools like this can play a vital role in improving research quality, reducing workload, and enabling broader participation in evidence-based research. However, structured evaluations involving multiple reviewers, real-world review topics, and cross-database comparisons in a structured manner would help increase the robustness, reproducibility, and time efficiency of this approach. Incorporating this framework into user-friendly interfaces, such as browser extensions or form-based tools, could further expand its accessibility, especially for novice reviewers. Future developments may extend this framework to accommodate more advanced querying needs and integrate with reference management and screening platforms.

Authors' contribution

Conceptualization: VY, TT; Methodology: VY, ADG; Formal analysis: VY, DD, TT; Investigation: VY, TT; Software: VY, UKM; Resources: ADG, MS, MB; Validation: ADG, MS;

Supervision: YDS; Writing – original draft: VY, TT, UKM, ADG, MS, MB, YDS; Writing – review & editing: VY, TT, UKM, ADG, MS, MB, DD, YDS.

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Disclosure statement

The authors report there are no competing interests to declare.

Data availability statement

The authors confirm that the data supporting the findings of this study are available within the article.

AI Use Disclosure

This study used ChatGPT (OpenAI; versions 3.5, 4, and 5) in generating suitable responses to specific prompts. The tools were used as part of the study design, data generation, and analysis of outputs. In addition, ChatGPT (OpenAI, version 5, May 2025 release) was used to improve the English grammar and readability of the manuscript. The authors confirm that all scientific ideas, interpretations, and conclusions are their own.

Supplementary files:

All supplementary materials, including the complete two-part prompt template (Word file), detailed methods, full pilot-testing results, and screenshots showing the execution of a sample search strategy, are available at https://github.com/ResearchCore/prompt2query.

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