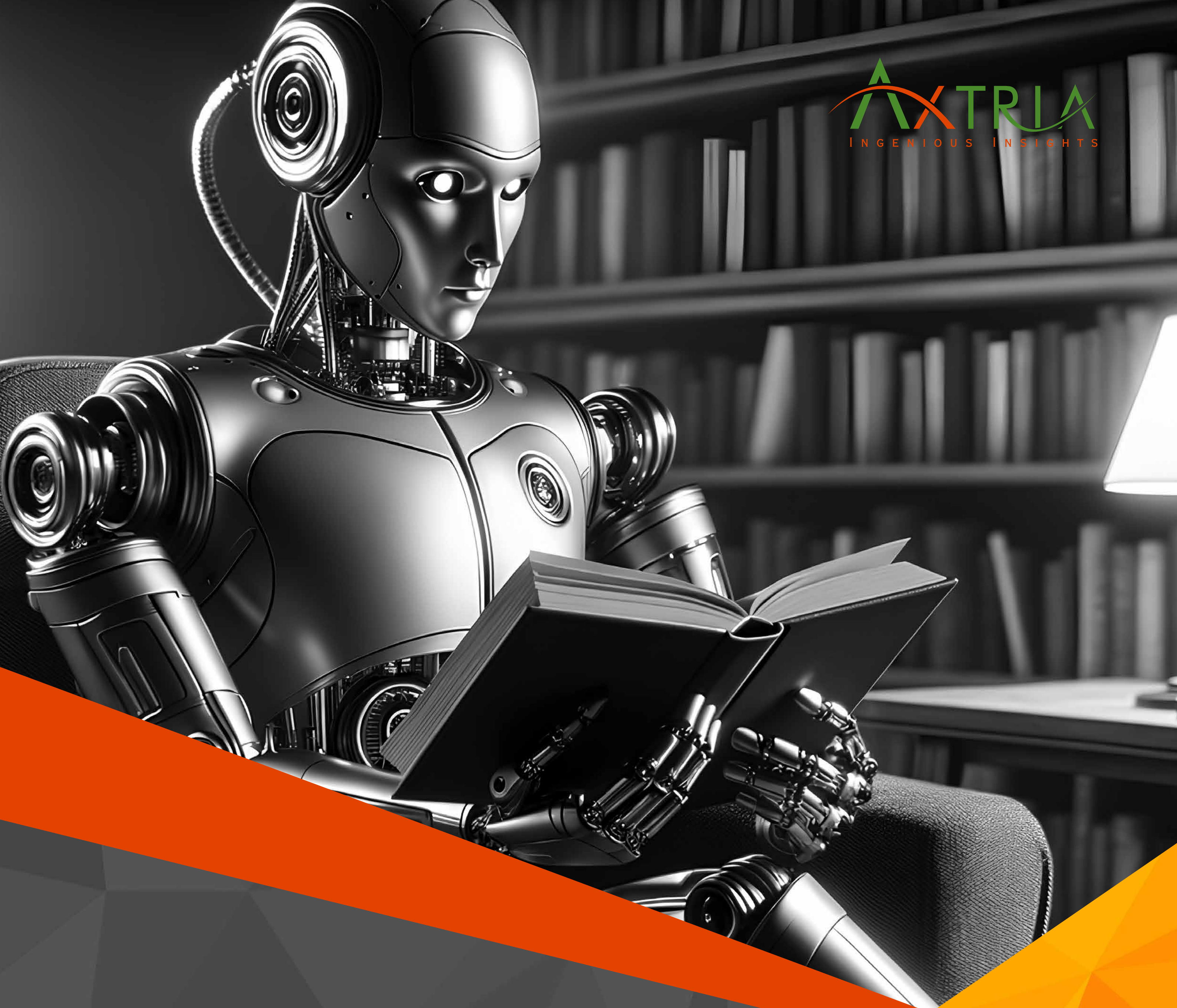

The Use of Natural Language Processing in Literature Reviews

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Abstract

Objectives: Literature reviews have many applications in health economics and outcomes research. However, they are limited in breadth and depth by the amount of time reviewers spend and are prone to human error and biases. Natural language processing (NLP) aims to address these issues. We reviewed the use of NLP in literature reviews, assessed its benefits and detriments, administered our own test case, and developed recommendations for future researchers.

Methods: To identify use cases and information on the use of NLP in literature reviews, we searched medical literature databases like PubMed, Science Direct, and Google Scholar; conference abstract lists; and other gray literature. The identified relevant studies are summarized herein. NLP was further implemented to conduct screening. Experts in systematic literature review were then consulted regarding the application of NLP to established literature review processes.

Results: When used to perform targeted literature reviews, NLP can reduce human labor, increasing the breadth and depth of literature reviewed at reduced costs. For systematic reviews, NLP can design and conduct searches, screen captured records, extract relevant information, and summarize key messages. However, NLP is not commonly deployed in an end-to-end fashion. NLP-based screening performs inconsistently, so screening decisions may conflict with those of humans. Our review of examples in the available literature found that match rates vary from 51% to 96% between studies. Often, NLP literature review methods do not comply with the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines, limiting their applicability. In our own NLP use case, we implemented a strong NLP engine to attain a 100% match rate with human reviewers while reporting reasons for inclusion and exclusion.

Conclusions: NLP can improve the breadth and depth of literature reviews while reducing human labor and the risk of bias and error. Literature reviewers should implement NLP cautiously, giving precise instructions and sufficient training, verifying NLP decisions, and following practice guidelines where possible.

1. Traditional Literature Review

1.1 Traditional Literature Review Applications and Processes

By providing specific information and a thorough summary of current research on a topic, literature reviews have become the foundation of many information-oriented processes within the life sciences. Literature reviews can help guide the efforts of researchers and pharmaceutical companies by providing information on the unmet needs of patients and current markets from clinical, economic, and humanistic perspectives. They can also provide information on current markets and inform market strategies. Evaluators such as regulatory and health technology assessments (HTA) bodies also rely heavily on literature reviews, which have helped to shape clinical guidelines and evaluate the effectiveness of treatments through statistical processes such as network meta-analysis.

Figure 1. Applications of Literature Review

Source: Axtria Inc.

Regardless of the intended application, literature reviews are crucial to scientific research, as they allow researchers to understand existing knowledge and contribute meaningfully to their field by avoiding the unintentional duplication of research and identifying gaps in it.[1] These ideas, among other benefits of literature reviews, are shown in Figure 2.

Depending on their purpose, targeted literature reviews (TLRs) vary in their degree of adherence to standardized literature review processes, as well as their scope and expertise. Researchers can quickly perform TLRs with simple searches or much larger reviews using complex searches and standardized methodologies, as is the case with systematic literature reviews (SLRs). The standard process of conducting any literature review begins with formulating the research question(s) to encompass the intended use case, such as any of those found in Figure 1. From that point, performing systematic searches using inclusion/exclusion (I/E) criteria adds to the complexity of the search, as does performing systematic retraceable searches using databases such as PubMed, Embase, Cochrane Library, Science Direct, Google Scholar, etc.

Figure 2. Importance of Literature Review in Scientific Research

Source: Axtria Inc.

Furthermore, researchers must screen titles, abstracts, and full texts to identify eligible studies. Beyond this, they extract data from the included studies and place them into evidence tables, which they then analyze to synthesize the evidence objectively in a balanced manner, summarizing the current state of knowledge.[2] These analyses can consist of robust statistical methods such as meta-analysis and indirect treatment comparisons that offer answers to questions that may otherwise prove unanswerable.

Due to their systematic and repeatable nature, many consider SLRs a more powerful source of evidence than TLRs.[3] Conversely, TLRs are valued for their rapid nature and freedom from strict, confining guidelines.

1.2 Challenges With Traditional Literature Reviews

While rigorous, the manual nature of traditional literature reviews poses several challenges. Searching research databases is laborious because of their required search syntax and differences in search syntaxes between databases. Screening abstracts and full texts requires large amounts of human labor, introduces the risk of citation bias,[4] and lacks transparency in the review methods, which can lead to further bias. Manual data extraction is a time-consuming process that is prone to human error. Such errors can then propagate into a subsequent analysis, which, if published, could receive citations in other articles and lead to many potential downstream effects. Additionally, due to the labor-intensive nature of SLRs, they are often not updated until necessary and can be impractical for topics with a large or rapidly evolving scope. Advances in computational tools and artificial intelligence (AI) may help overcome some of these difficulties.

Although TLRs are unencumbered by SLRs' rigorous guidelines, they, too, face several challenges. Unlike SLRs, which inherently provide broader coverage across diverse topics, TLRs offer the advantages of efficiency and reduced labor by enabling researchers to address specific questions or delve deeply into areas of interest. However, this efficiency comes at the cost of reduced research scope, rendering TLRs narrower and shallower than SLRs. Expectedly, TLRs are limited in both breadth and depth by the amount of time and effort spent by reviewers.

2. Natural Language Processing

2.1 Introduction to Natural Language Processing

In its infancy, natural language processing (NLP) involved basic text analysis like keyword frequency and stop word (such as "and/or") removal using rule-based approaches. These foundational methods paved the way for machine learning (ML) and AI in text analysis. Transitioning from rule-based methods, NLP embraced ML and enabled computers to learn directly from text data. With architectures like transformers that enhanced language model capabilities, NLP then evolved to integrate deep learning, resulting in improved comprehension and human language generation.

Natural language processing now stands at the crossroads of computer science and linguistics, aiming to make machine-human language interaction seamless. Recent advancements, propelled by deep learning, have transformed industries from healthcare to finance. Yet challenges such as handling ambiguity and cultural nuances persist, necessitating continuous research and the enhancement of algorithms and datasets.

2.2 Large Language Models

Large language models (LLMs) have significantly enhanced AI and NLP. These models are designed on the foundations of ML, neural networks, and extensive data processing. Their primary function is to understand, generate, and manipulate human language, preparing them for various language-related tasks.

The core capabilities of LLMs are extensive. They can perform a vast range of tasks, including text generation, translation, summarization, question-answering, and sentiment analysis. These models are versatile, and they excel at contextual understanding, making them ideal for use in chatbots, content generation, and data analysis. They can comprehend and generate text in multiple languages and adapt to various domains. Previous studies assessed how patients and clinicians use different vocabularies,[5] and LLMs will give researchers the tools they need to merge these dialects for better communication and understanding. They can also adjust these models for specific applications, allowing personalized and context-aware responses.

3. Applying Natural Language Processing to Literature Reviews

3.1 Targeted Literature Review

Researchers can leverage NLP to facilitate and assist in conducting TLRs in several novel ways. NLP techniques can automate some of the initial literature search and screen articles for relevant information. Rather than relying on manual searches or predefined keywords, NLP tools allow querying across full-text databases using semantic searches and extracted key phrases.[6] This technique allows researchers to cast a wider initial net that captures more relevant papers. By leveraging NLP-based document clustering and classification methods, the literature review conductors can automatically group retrieved papers by topic and relevance,[7] providing a high-level overview of the literature and helping identify areas where evidence may be lacking. By automating these initial steps of literature gathering and organization, researchers can focus on a deeper review and analysis of the identified papers while mitigating the burden of costs, time, and manual labor.

Although TLRs facilitated by NLP allow reviewers to capture a broader range of evidence around a specific research question, users must still take care when constructing search queries to avoid missing relevant articles that differ in their phrasing. Inefficiencies in the automation pipeline may also occur because of inadequate preparation when synthesizing a research question. To improve the consistency, accuracy, and speed of human and NLP labor, experts at leading literature review software firms strongly suggested that researchers refrain from using open-ended or ambiguous research questions.[8] Still, some human screening is essential to validate NLP-based results. There are limited studies on the ability of NLP to accurately interpret the complex semantic relationships in academic text, such as NLP's ability, or inability, to map specific keywords and phrases to concepts.[9] However, overall, NLP-aided literature reviews facilitate the rapid identification of relevant articles to aid in evidence-based research.

3.2 Systematic Literature Review

When used appropriately, reviewers can further harness the power of NLP to help with several steps in the SLR process.[10] First, by learning the semantics and operators required for each database, NLP can alleviate the laborious traditional process of constructing unique search strings for different databases. After completing the search process, NLP can further reduce the labor involved with traditional reviews by eliminating the need for title-and-abstract screening, thus moving directly to screening full texts. However, some manual screening is still required to validate classifier decisions in terms of which articles are included and excluded during screening. This adds another layer of statistical analysis, particularly in establishing quantitative measurements on the overall level of agreement between the reviewer and AI. At this point, the user can instruct NLP technology to extract and classify important information from the chosen articles and then summarize the information into clear and concise conclusions. Researchers have reported that implementing a semi-automated approach as described can reduce the workload by 30-70%.[11] Another investigation showed that using an NLP-assisted abstract screening tool produced a 45.9% reduction in screening time per abstract and decreased inter-reviewer conflict rates.[12]

Every systematic review's primary goal is to rapidly gather a comprehensive evidence base in response to a focused research question. Such evidence bases are necessary for generating summaries of available evidence in the literature, such as dossiers created according to the Academy of Managed Care Pharmacy guidelines. Researchers can spend more effort on in-depth critical appraisal and synthesis by automating the initial literature search and screening. Beyond conducting the traditional steps of SLR, reviewers can employ NLP technology to identify and prioritize certain articles,[13] automatically subgrouping the entire search by sub-topic and relevance if desired, to help focus reviewer efforts on the publications most relevant to their research question.

Two important disadvantages of using NLP for SLR are that some applications require technical expertise, and others require manual user review to validate the academic text. NLP-powered SLRs might also encounter difficulties in evaluating study quality beyond predefined parameters. Thus, NLP could require substantial manual customization to adapt to various research questions, potentially leading to the misclassification of studies because of rigid quality criteria. Moreover, while using NLP can involve lower costs than primary research, the initial preparation of automation and having researchers perform manual labor for validation are still expensive.[14]

Another limitation is that, even with thorough calibration and today's advanced LLMs, AI screening decisions may not consistently align with those made by human reviewers.[15] It is crucial to carefully examine the discrepancies between the decisions of AI and human reviewers since even human criteria can lead to inaccurate screening choices. Finally, while implementing third-party AI services, the adopted AI tools may not adhere to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, as the developers may not incorporate them in the development process. Despite this, overall, NLP facilitates more rapid, comprehensive, and well-updated systematic reviews. There are also promising applications and features being developed that add a second NLP screener rather than using human researchers to validate results.[16] The key advantages and disadvantages of implementing NLP methods in literature reviews, either alone or in combination with human direction, are summarized in Table 1 below.

Table 1. Comparison of Methods for Targeted and Systematic Literature Reviews

	Targeted Literature Review Conductors		
	Human	**AI**	**Human/AI Combination**
Pros	• Ability to understand context and nuances • Capable of making intuitive judgments • Can handle ambiguous or poorly structured data	• Fast processing of large volumes of data • Consistent application of criteria • Less prone to fatigue	• Combines human intuition with AI efficiency • Can improve the selection process through iterative learning • Reduces bias through AI consistency while retaining human critical thinking
Cons	• Time-consuming, subject to bias • Potentially less comprehensive due to selective focus	• May miss nuances or non-explicit connections • Requires high-quality training data • Can struggle with ambiguous information	• Requires well-defined protocols for effective collaboration • Can be costly to set up and maintain. May have issues with the integration of human and AI decision-making
	Systematic Literature Review Conductors		
	Human	**AI**	**Human/AI Combination**
Pros	• Deep comprehension of study quality and relevance • Capable of sophisticated synthesis of findings • Can navigate complex methodologies within studies	• Can rapidly screen titles and abstracts • Can apply consistent I/E criteria • Manages large datasets and multiple databases with ease	• AI increases the speed of initial screening processes, while humans ensure the final selection's quality and relevance • Allows for a more robust and reproducible review process with high decision-match rates
Cons	• Very labor-intensive • May be influenced by individual or group biases • Time constraints can affect comprehensiveness and depth	• Limited ability to assess the quality of studies beyond predefined parameters • May require extensive customization to handle different research questions • Potential for missing relevant studies due to rigid criteria • Lack of exclusion decision reporting and non-adherence to PRISMA guidelines	• Can be challenging to balance the input from AI and humans • Iterative process of refining AI parameters can be time-consuming • Integration of qualitative data may still rely heavily on human analysis

Source: Axtria, Inc.

3.3 Previous Applications of NLP to Literature Review

A recent presentation at the International Society for Pharmacoeconomics and Outcomes Research (ISPOR) analyzed the potential of NLPs to assist with the SLR process.[20] In that analysis, three LLMs (AI21 Ultra, OpenAI GPT-4, Google Vertex AI Model Bison) were deployed to perform SLRs. Their results were compared with responses from human reviewers as references. The LLMs measured the performance and used a metric called the "decision match rate" to analyze the I/E decisions and determine the number of LLM decisions that were identical to those of a human reviewer. The results of five sample screening decisions showed a decision match rate of 71%, derived from the confusion matrices that compared GPT-4 with the human reviewer, outperforming AI21 Ultra (51.0%) and Model Bison (67.7%).[20]

In the face of larger volumes of publications and the increasingly rigorous requirements of health technology assessment bodies, the authors of an ISPOR poster[17] explored the utility of AI in assisting with SLRs for submission. Human researchers were asked to complete two SLRs. One independent researcher was available to resolve disagreements. DistillerAI mirrored their work, and these findings were compared against those of humans. After assessing 3,201 screening decisions, DistillerAI and humans scored 77-84% for overall inter-rater reliability (IRR), which measures the level of agreement between human reviewers and AI. The level of agreement further improved to 82-92% by exposing the AI to more training data.[17]

Another SLR examined how AIs ran or assisted with SLRs. The authors evaluated the use of AI, including AI-as-a-service applications (AIsAPPs), like DistillerAI, in the MEDLINE and Embase databases. This investigation revealed that, while AIsAPP capabilities were being employed in SLRs, there was no concrete evidence that they adhered to PRISMA guidelines, further limiting their usefulness.[18]

A recent ISPOR abstract shows that utilizing AI classifiers for systematic reviews potentially saved researchers 50-60% of human working hours,[20] with a relatively high (87.5%) level of agreement between AI and human researchers. Likewise, another study using PubMed BERT demonstrated a 45.9% decrease in screening time per abstract and reduced inter-reviewer conflict rates at the same time.[13] However, the AI classifier could not provide reasons for its exclusions, so it violated PRISMA guidelines, limiting its applicability.[19]

3.4 Axtria's Use Case for NLP in Literature Review

To expand upon the previous uses of NLP in the literature review described above, we applied the GPT-4 AI model to screen a sample of articles. Past uses of NLP in literature review have not consistently adhered to PRISMA guidelines and lacked predefined population, intervention, comparator, outcome, and study design (PICOS)[20] criteria or did not report reasons for each exclusion. We maintained alignment with PRISMA guidelines and used predefined PICOS criteria to address the first two issues. We then provided the AI model with the appropriate I/E criteria for reviewing the abstracts and instructed the model to give the reason behind each I/E decision. After GPT-4 screened the abstracts, we administered quality control checks on the output before finalizing decisions. This involved manually reviewing a sample of the AI's I/E decisions and justifications to ensure accuracy and adherence to the I/E criteria. Through this process, we found that the AI model correctly applied the I/E criteria for all the abstracts reviewed in the quality control sample. The model attained 100% accuracy for our final group of 80 articles. Other studies using AI models obtained 51% - 96% accuracy after analyzing samples of approximately 400 to 3,200 articles.[13, 20, 21, 22, 23] A potential reason for the greater accuracy in our study compared to others is that the GPT-4 model adopted in our study may have higher accuracy than the other models, as demonstrated in a study by Hemant et al.[15] In addition, the study sample our model screened may have been more homogenous than those analyzed by other models, as over 90% of articles screened in our study were included, based on our I/E criteria. However, as a proof-of-concept, this effort demonstrated that a trained reviewer could leverage AI's automated screening and justification abilities to streamline the screening process while maintaining accuracy.

4. Conclusion and Recommendations on the Use of NLP in Literature Reviews

There are many promising developments in NLP applications for literature review synthesis, which can improve the depth and breadth of literature reviews while reducing human labor and the risk of bias and error. Previous applications of NLP reviewed herein, as well as our own test case, have demonstrated these benefits. However, NLP users still need to consider and address the limitations of applying NLP. Since the NLP models' accuracy and reliability vary, researchers are justified in manually administering routine spot-checks and screening portions of the automated literature review process to validate their models. NLP models often do not comply with published guidelines, such as PRISMA's, which further limits their applicability in research.

Additionally, because NLP models are highly sensitive to the structure of search queries and prompts, we recommend that researchers act prudently when drafting them and remain cognizant of their personal biases to ensure that they do not misdirect or distract the NLP model from the research question. This practice will also mitigate the potential for future downstream errors. For example, the program may omit relevant papers that use different phrasing despite the strength of NLP's semantic search capability. As more sophisticated NLP model versions are still in development, it is recommended that users maintain awareness of the historical limitations, including residual biases and longer run times for some applications. Lastly, optimal NLP usage in literature review synthesis necessitates a certain degree of technical expertise in conjunction with a strong knowledge of scientific and medical writing. Therefore, we recommend consultation with technical and clinical experts when implementing NLP in literature reviews.

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