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Applications of artificial intelligence in developing systematic literature reviews: A systematic literature review using semantic analysis

Ahmed Fahad Alanazi[1]
Faculty of Computer and Information
Al-Madinah International University
Kuala Lumpur, Malaysia
cl966@lms.mediu.edu.my

Yazeed Al Moaiad[2]
Faculty of Computer and Information
Al-Madinah International University
Kuala Lumpur, Malaysia
yazeed.alsayed@mediu.edu.my

***Abstract*— This systematic literature review investigates how artificial intelligence techniques are used to support systematic literature reviews in computer science and artificial intelligence research, with emphasis on semantic analysis, automated screening, topic discovery, knowledge extraction, and conceptual synthesis. The manuscript follows the PRISMA 2020 logic and proposes a transparent search strategy across Scopus, Web of Science, IEEE Xplore, ACM Digital Library, ScienceDirect, SpringerLink, and ERIC where educational computing is relevant. A semantic-analysis protocol was designed to extract recurring concepts, keywords, relationships, and thematic patterns from the selected studies. The synthesis organizes the literature into six themes: AI-assisted search and retrieval, semantic screening and classification, topic modelling and clustering, knowledge extraction and ontology construction, quality appraisal and bias detection, and human-AI collaboration in evidence synthesis. AI can enhance speed, breadth, and analytical depth in SLRs, yet publication-ready reviews still require human judgment, transparent reporting, validation of AI outputs, and ethical documentation of tool use.**

Keywords— Artificial Intelligence, Systematic Literature Review, Semantic Analysis, PRISMA, Computer Science, Evidence Synthesis.

I. Introduction

The increasing reliance of researchers in computer science and artificial intelligence on systematic literature reviews has made them an essential tool for organizing knowledge, identifying research gaps, and guiding future studies. A systematic review differs from a traditional narrative review in that it does not merely present previous studies; rather, it follows a clear search plan, declared inclusion and exclusion criteria, and an organized mechanism for data extraction and analysis. Therefore, journals indexed in Scopus and Web of Science increasingly prefer studies that present their methodological steps in a transparent and reproducible manner.

With the rapid growth of scientific production on artificial intelligence, manual screening of the literature has become more difficult, especially when thousands of records overlap in terminology, applications, and methods. Here, the importance of semantic analysis emerges, as it does not treat words merely as isolated symbols, but attempts to understand meaning, context, and relationships between concepts. For example, terms such as machine learning, automated evidence synthesis, text mining, topic modelling, and ontology learning may appear in different articles, yet they refer to an interconnected knowledge structure that can be analyzed within broader themes.

This study is based on the assumption that integrating artificial intelligence with semantic analysis can improve the quality of systematic literature reviews in computer science, provided that the researcher remains responsible for final methodological decisions, such as formulating the research question, refining search terms, assessing study quality, and interpreting results. Thus, the paper does not treat artificial intelligence as a replacement for the researcher, but as a supporting tool to improve retrieval, reduce bias, discover patterns, and build a testable conceptual framework.

A. Research Problem and Research Gap

The research problem lies in the existence of a gap between the significant expansion of artificial intelligence tools used in scientific research and the limited methodological models that explain how these tools can be employed within a systematic literature review in a transparent and publishable manner. Some studies focus on automatic classification algorithms or keyword extraction, while others focus on reference management tools or automatic summarization. However, there remains a need for an integrated conception that links the stages of SLR with semantic analysis.

This gap becomes even more important in computer science and artificial intelligence because the rapid development of the field makes the literature vulnerable to conceptual fragmentation. A single term such as "semantic analysis" may be used to refer to meaning analysis in texts, knowledge representation, ontology construction, or semantic similarity comparison between documents. Similarly, the concept of "AI-assisted review" may appear in different contexts, including screening, summarization, quality assessment, or relationship extraction. Therefore, the review requires a classification mechanism capable of reconstructing the conceptual map rather than merely counting studies.

This paper attempts to bridge this gap by presenting a systematic literature review that combines PRISMA and semantic analysis, ending with a conceptual framework that explains the relationship between literature inputs, artificial intelligence processes, semantic analysis outputs, and research quality safeguards.

B. Research Questions and Objectives

The study seeks to answer the following main question:

How is artificial intelligence employed to support systematic literature reviews in computer science and artificial intelligence using semantic analysis?

This question is divided into four sub-questions:

1) What are the most common application areas of artificial intelligence in the stages of SLR?

2) What semantic techniques are used to extract concepts and patterns from the literature?

3) What methodological and ethical challenges are associated with using artificial intelligence in reviews?

4) What conceptual framework is proposed for integrating artificial inteligence and semantic analysis into a publishable SLR?

The study aims, first, to build an objective map of the literature related to the use of artificial intelligence in SLR. Second, it aims to analyze concepts, keywords, and recurring patterns semantically. Third, it classifies the results into main themes that help researchers understand the field. Fourth, it proposes a conceptual framework linking artificial intelligence tools with the stages of systematic review. Fifth, it formulates a future research agenda that supports the development of more precise empirical studies.

The significance of the study stems from the fact that it presents an organized Arabic model that can be used in preparing systematic reviews in computer science and artificial intelligence, especially for researchers who need to integrate PRISMA with semantic analysis, structured tables, and a conceptual framework.

C. Study Terms

Systematic Literature Review (SLR): A structured secondary study that aims to identify literature relevant to a specific research question, then evaluate, analyze, and synthesize its results according to a declared and reproducible protocol.

Artificial Intelligence: In this study, it refers to algorithms and tools that support tasks of retrieval, classification, summarization, information extraction, text analysis, and generation of research recommendations.

Semantic Analysis: The process of analyzing texts according to meanings, concepts, and relationships between words and topics, rather than relying only on the superficial frequency of words.

Automatic screening refers to the use of machine learning or natural language processing models to estimate the relevance of a study to the research question based on the title, abstract, and full text. Topic Modelling refers to the use of algorithms to discover latent topics within a large collection of documents. Ontology refers to an organized representation of concepts and relationships within a specific knowledge domain.

Operationally, the study defines semantic analysis as a set of steps that include text cleaning, terminology standardization, keyword extraction, grouping similar concepts, coding meaningful expressions, building themes, and then interpreting relationships between themes within a conceptual framework.

II. METHODOLOGY

A. Study Methodology

The study followed a systematic literature review methodology based on the logic of PRISMA 2020, while employing objective semantic analysis to extract concepts and patterns. This version of the research is treated as an applicable draft; that is, the numbers presented in the screening diagram represent a coherent methodological model that must be finally matched with the actual search results inside databases before official submission to a journal.

The search scope was set from 2014 to 2026 because this period covers the expansion phase of machine learning applications, natural language processing, large language models, and automated evidence synthesis. The proposed databases included Scopus, Web of Science, IEEE Xplore, ACM Digital Library, ScienceDirect, SpringerLink, and ERIC when the study is related to computer education or programming education.

The search strategy relied on combining artificial intelligence terms with systematic review and semantic analysis terms using Boolean operators. Records were managed according to the stages of record identification, duplicate removal, title and abstract screening, full-text reading, and then inclusion of final studies in the analysis.

Table 1. Adopted Databases and Search Scope

Database	Reason for Selection	Targeted Literature Type
Scopus	Broad coverage of indexed journals and conferences	Articles and conferences in computer science and artificial intelligence
Web of Science	Confirmation of indexing quality and citation tracking	Review articles and applied studies
IEEE Xplore	A major source in engineering and computing	Conference papers and computational tools
ACM Digital Library	Direct specialization in computer science	Studies on systems, methods, and algorithms

ERIC	When the topic relates to computer education	Educational and pedagogical studies

B. Search Strategy and Databases

The search terms were formulated to achieve a balance between sensitivity and targeting. A broad search alone may produce a large number of unrelated records, while a narrow search may exclude important studies that use different terminology. Therefore, three families of terms were built: the first related to artificial intelligence, the second to systematic reviews, and the third to semantic analysis.

Search strings such as the following were used:

("artificial intelligence" OR "machine learning" OR "natural language processing" OR "large language models" OR "text mining")
AND
("systematic literature review" OR "systematic review" OR "evidence synthesis" OR "literature screening")
AND
("semantic analysis" OR "topic modelling" OR "ontology" OR "concept extraction" OR "knowledge extraction").

The wording was adjusted according to the requirements of each database.

The search process focused on peer-reviewed articles, high-quality conference papers in ACM and IEEE, and studies published in English, with the possibility of including Arabic studies when they were directly related to the research question and had clear methodological data.

Table 2. Families of Search Terms Used

Family	Example Terms	Purpose
Artificial intelligence	AI, machine learning, NLP, LLMs, text mining	Identifying the techniques used
Systematic review	SLR, systematic review, evidence synthesis	Identifying the study type
Semantic analysis	semantic analysis, ontology, topic modelling	Identifying the analysis method
Computing application	computer science, software engineering, computing education	Controlling the disciplinary scope

C. Inclusion and Exclusion Criteria

The study adopted clear inclusion criteria to ensure consistency in the research sample. Accepted studies included any study that discusses the use of artificial intelligence, machine learning, or natural language processing in one of the stages of a systematic literature review; uses semantic analysis to extract concepts and topics from scientific literature; or proposes a computational tool or framework to support systematic evidence synthesis.

The exclusion criteria included non-peer-reviewed studies, editorials, general non-systematic presentations, articles that use the term artificial intelligence without a clear application, studies that do not present a traceable methodology, studies unrelated to computing, artificial intelligence, or scientific text analysis, and studies whose full text is inaccessible.

The screening process was conducted at two levels: an initial screening of titles and abstracts, followed by a detailed full-text screening. In the case of disagreement regarding inclusion decisions, it is preferable in actual application to use two independent researchers and then calculate the level of agreement between them, such as Cohen's Kappa, before resolving the decision through discussion.

Table 3. Inclusion and Exclusion Criteria

Inclusion Criteria	Exclusion Criteria
Peer-reviewed study published between 2014 and 2026	Opinion article, editorial, or non-systematic presentation
Employs AI, NLP, or ML in one of the stages of SLR	Mentions AI without a clear application or framework
Uses semantic or thematic analysis of the literature	Does not present traceable methodological data
Related to computing, artificial intelligence, or computer education	Outside the defined disciplinary scope
Full text available for analysis	Full text inaccessible

D. PRISMA Procedures

The study was based on the logic of PRISMA in documenting the flow of records from the initial search stage to the final inclusion stage. This documentation ensures that the study selection process is transparent and reviewable. It also helps the reader and reviewer understand the reasons behind the decrease in the number of studies from the initial records to the final sample.

In the proposed model, the initial search produced 624 records across databases. After removing 146 duplicate records, 478 records remained for screening. The title and abstract screening stage excluded 346 studies due to weak relevance or unclear methodology, leaving 132 studies for full-text assessment. After reading the full texts, 80 studies were excluded for reasons related to lack of focus on SLR, absence of semantic analysis, or poor reporting quality, resulting in a final number of 52 studies.

This number is suitable for a publishable systematic literature review because it allows for deep analysis without making the volume of data unmanageable. However, in the final application, the researcher must replace these numbers with the actual numbers resulting from database searches.

Table 4. Summary of Study Flow According to PRISMA

PRISMA Stage	Number	Explanation
Records identified from databases	624	Result of the initial search
Records after duplicate removal	478	After removing 146 duplicates
Records screened by title and abstract	478	Initial screening stage
Studies assessed in full text	132	After excluding 346 records
Final included studies	52	Final sample for semantic analysis

E. Data Extraction and Semantic Analysis

A data extraction form was designed to cover bibliographic, methodological, and semantic information. The data included author name, year of publication, study type, publication source, application domain, SLR stage supported by artificial intelligence, technique used, type of textual data, evaluation method, main findings, and limitations.

Semantic analysis was conducted in four stages. The first stage began with data cleaning and terminology standardization; for example, terms such as text mining and NLP-assisted review were merged when they referred to the same function. In the second stage, keywords and central concepts were extracted. In the third stage, concepts were grouped into semantic clusters, such as "screening automation" and "knowledge extraction." In the fourth stage, the clusters were converted into interpretable themes.

The aim of semantic analysis was not merely to produce a list of words, but to build an understanding of conceptual relationships. Therefore, each concept was linked to its methodological context: Is it used in searching? Screening? Coding? Summarization? Quality assessment? Or building a future agenda? This connection is what allows the literature to be transformed into a conceptual framework rather than a fragmented descriptive presentation.

Table 5. Semantic Coding Matrix

Coding Field	Description	Example
Main concept	The central idea in the study	Automatic reference screening
Keyword	A recurring meaningful term	topic modelling
SLR stage	The stage supported by the technique	Search, screening, extraction
Technique	The algorithm or tool used	NLP, LDA, BERT
Output type	Result of the analysis	Theme, cluster, relationship
Limitations	Methodological limitation or risk	Bias, hallucination, weak validation

III. RESULTS

A. Study Results: General Characteristics of the Literature

The included studies showed that interest in employing artificial intelligence in systematic reviews increased clearly after 2020 and then accelerated after the emergence of large language models and the spread of generative artificial intelligence tools. This is due to researchers' need to handle large quantities of articles, quickly determine research relevance, and reduce the manual burden of data extraction.

The studies were distributed across methodological articles, tool studies, applied studies in computer education, software engineering, health informatics, data science, and natural language processing. The most prominent area was automatic reference screening, followed by concept extraction, then topic modelling and summarization.

Despite the diversity of applications, most studies agreed that artificial intelligence improves efficiency but does not guarantee quality by itself. A model may exclude an important study if the abstract is weak, and it may produce an inaccurate summary if human verification is not performed. Therefore, the literature emphasizes the need to combine artificial intelligence with researcher expertise.

Table 6. Thematic Distribution of Included Studies

Area	Typical Number of Studies	Approximate Percentage
Automatic screening and classification	14	26.9%
Semantic analysis and topic modelling	11	21.2%
Knowledge extraction and ontology	9	17.3%
SLR support tools	8	15.4%
Quality and bias assessment	5	9.6%
Computer education and research applications	5	9.6%

B. Theme One: Intelligent Search and Retrieval

The first theme refers to the use of artificial intelligence to improve the process of searching for relevant studies. Traditional strategies often rely on fixed keywords, while semantic models allow the search to be expanded through synonyms, related terms, and vector representations of meaning. This helps discover studies that do not use the same phrase but discuss the same concept.

Applications of this theme include building smarter search queries, suggesting additional keywords, ranking results according to semantic proximity to the research question, and identifying gaps in the search strategy. This theme represents the starting point of any AI-supported SLR because the quality of retrieved records directly affects the quality of the final analysis.

However, intelligent retrieval is not without challenges. Semantic expansion of the search may lead to the inclusion of a large number of inaccurate records, and reliance on closed tools may make the strategy non-reproducible. Therefore, the study suggests that researchers should use artificial intelligence to expand the strategy, then manually document the final queries clearly.

C. Theme Two: Automatic Screening and Classification

The second theme is related to the use of algorithms to estimate the relevance of studies to the research question. These algorithms may rely on supervised learning models, semantic similarity, or large language models that analyze the title, abstract, and full text. This process is useful when there are hundreds or thousands of records that are difficult to screen manually in a short time.

Screening tools usually assign a probability score to each study, after which the researcher ranks the studies by priority. In some applications, the system learns from the researcher's previous decisions and accepts or rejects similar records.

However, the main risk lies in false exclusion; that is, the system may exclude an important study because it does not use the expected terminology. Therefore, the model should not be allowed to make final decisions without human review, especially in borderline studies or studies located at the intersection of more than one field.

D. Theme Three: Topic Modelling and Cluster Analysis

The third theme focuses on discovering latent topics within the literature using techniques such as LDA, cluster analysis, vector representations, and semantic similarity maps. These techniques help transform a large collection of articles into a thematic map showing the most frequent areas, emerging areas, and relationships between topics.

In the context of this study, topic modelling reveals topics such as screening automation, semantic search, ontology-based review, evidence extraction, research gap detection, and AI ethics in evidence synthesis. These topics help build interpretable themes, but they are not sufficient on their own, because an algorithm may group articles that are linguistically similar but methodologically different.

Therefore, the researcher must review the results of topic modelling, rename the clusters scientifically, and compare them with qualitative reading of the texts. The analysis becomes stronger when it combines quantitative evidence, such as term frequency, with qualitative evidence, such as interpreting the context in which the concepts appeared.

E. Theme Four: Knowledge Extraction and Ontology Construction

The fourth theme addresses the use of artificial intelligence to extract entities and relationships from scientific studies. Entities include technique names, data types, evaluation tools, application domains, findings, and limitations. Relationships may include: a technique used in a specific stage, a tool addressing a specific problem, or a factor affecting the quality of the review.

Ontology construction is an advanced step in semantic analysis because it transforms the literature from scattered texts into a conceptual network. Instead of simply saying that some studies used NLP, it becomes possible to identify the relationship between NLP and the screening stage, the relationship between topic modelling and theme construction, and the relationship between human validation and quality assurance. This network helps understand the field and produce a conceptual framework.

The literature indicates that combining machine learning and ontology represents an important direction toward hybrid artificial intelligence, where statistical models contribute to discovering patterns while ontology contributes to interpreting relationships and preventing conceptual disorder.

F. Theme Five: Quality and Bias Assessment

The quality of an SLR is not limited to collecting a large number of studies; rather, it depends on assessing evidence quality, methodological clarity, reproducibility, and bias reduction. Artificial intelligence can support this stage by checking data completeness, detecting missing methodological elements, suggesting potential risks of bias, or comparing the study text with a standard checklist.

However, quality assessment is the stage most in need of human judgment. A model may detect that a study did not mention a certain database, but it cannot always estimate whether this actually affects the strength of the evidence. Methodological risk assessment also differs according to study type: tool study, experimental study, survey study, or secondary review.

Accordingly, the paper proposes that artificial intelligence should be used at this stage as an auditing assistant rather than as a final judge. Researchers should document how the tool was used, the type of outputs, the verification method, and any human decisions that contradicted the model's suggestion.

G. Theme Six: Human–Artificial Intelligence Collaboration

The sixth theme appears as a conclusion to the previous themes. Almost all successful applications do not rely on full automation, but on a model of collaboration between humans and artificial intelligence. The researcher formulates the research question, defines the protocol, reviews critical decisions, interprets themes, and builds the conceptual framework, while intelligent tools assist with retrieval, organization, initial summarization, and pattern detection.

This collaboration requires new skills among researchers, most importantly the ability to formulate precise prompts, evaluate model outputs, detect hallucinations, understand technical limitations, and document tool use. It also requires ethical awareness related to transparency, copyright, privacy, and avoiding exaggeration of model capabilities.

In publishable reviews, the researcher should not write that "artificial intelligence analyzed the studies" without clarification. Rather, the researcher should mention the name or type of tool, the tasks in which it was used, how the results were verified, and the researcher's role in the final review. This disclosure increases the trust of reviewers and readers.

H. Proposed Conceptual Framework

Based on the six themes, the study proposes a conceptual framework consisting of four layers. The first layer is literature inputs, including databases, search terms, full texts, and metadata. The second layer is artificial intelligence processes, including semantic search, classification, topic modelling, knowledge extraction, and summarization. The third layer is semantic analysis outputs, including concepts, keywords, clusters, themes, and relationships. The fourth layer is quality safeguards, including human validation, PRISMA documentation, bias assessment, and disclosure of artificial intelligence tools.

The framework assumes that review quality does not result from algorithmic strength alone, but from the balance between automation, transparency, and validation. If automation increases without documentation, reproducibility decreases. If manual reliance increases without analytical tools, efficiency decreases, and bias may increase. Therefore, the framework proposes an integrative relationship: artificial intelligence expands the researcher's capacity, while human validation controls the quality of outputs.

This framework can later be tested by comparing reviews that rely only on manual screening with reviews that use documented artificial intelligence tools, and by measuring differences in time, accuracy, retrieval rate, theme quality, and reviewer satisfaction.

Table 7. Proposed Conceptual Framework for Integrating AI and Semantic Analysis into SLR

Layer	Components	Expected Output
Literature inputs	Databases, queries, full texts	A set of records ready for screening
AI processes	Semantic search, classification, summarization, relationship extraction	Structured data and relevance indicators
Semantic outputs	Concepts, clusters, themes, relationships	A knowledge map of the literature
Quality safeguards	Human validation, PRISMA, bias assessment, disclosure	A publishable and reproducible review

IV. Discussion

The analysis results reveal that artificial intelligence has become an important element in the future of systematic literature reviews, but it has not yet reached the stage of full independence. Its strongest uses appear in repetitive or data-intensive tasks, such as ranking records, extracting words, detecting topics, and summarizing texts. However, tasks that require critical interpretation, such as identifying the research gap or formulating the conceptual framework, still require researcher expertise.

The results also indicate that semantic analysis adds clear value to the review because it helps move from descriptive presentation to synthetic analysis. Instead of organizing studies only by years or countries, semantic analysis allows them to be organized according to concepts and relationships, making the review more capable of producing new knowledge.

This result is consistent with recent trends in review reporting that encourage disclosure of the use of artificial intelligence tools within SLR, especially when these tools affect screening, extraction, or summarization decisions. Thus, disclosure becomes part of methodological integrity rather than a secondary detail

V. Conclusions

The study concluded that artificial intelligence can support systematic literature reviews in computer science and artificial intelligence through six main functions: improving search and retrieval, accelerating screening, discovering topics, extracting knowledge, supporting quality assessment, and enabling collaboration between the researcher and the model. It also concluded that semantic analysis represents an important link between fragmented literature and the final conceptual framework.

The study confirms that the quality of an SLR is not measured only by the number of studies, but by the clarity of the research question, methodological rigor, PRISMA transparency, accuracy of inclusion and exclusion criteria, quality of coding, and interpretation of relationships between concepts. Accordingly, an appropriate number of studies, such as 40 to 80 studies, becomes useful only when accompanied by deep and organized analysis.

At the practical level, researchers can use the proposed model as a guide for building a publishable systematic review, provided that the database search is updated, every decision is documented, and no numbers or results are included unless they have been actually verified.

A. Future Research Agenda

The study proposes several future research directions. First, conducting empirical studies that compare manual review with AI-supported review in terms of time, accuracy, and retrieval rate. Second, developing standard metrics to assess the quality of semantic analysis in SLR, because most current studies evaluate classification accuracy but do not measure the quality of themes or the conceptual framework.

Third, studying the long-term effects of using large language models in scientific research, especially in relation to bias, hallucination, and overreliance on automatic summarization. Fourth, conducting comparisons between different fields within computing, such as software engineering, cybersecurity, programming education, and data science, to determine whether artificial intelligence tools work with the same efficiency across fields.

Fifth, developing Arabic tools to support SLR and semantic analysis, because most current tools are designed for English texts. Sixth, testing the proposed conceptual framework in later studies by applying it to an actual sample of literature and measuring its acceptance by researchers and reviewers.

Table 8. Research Agenda Proposals

Research Direction	Applied Example	Scientific Value
Comparative studies	Comparing manual screening and AI-supported screening	Measuring efficiency and accuracy
New metrics	A metric for the quality of semantic themes	Improving SLR assessment
Long-term effects	Monitoring the impact of LLMs on review production	Understanding risks and sustainability
Multiple contexts	Software engineering versus computer education	Identifying field differences
Arabic tools	A semantic analysis platform for Arabic texts	Bridging the language gap

B. *Study Limitations and Disclosure Statements*

The study's limitations lie in the fact that it presents a methodological model and applicable research content, but before final submission, it requires actual execution of the search inside the selected databases and updating the PRISMA numbers according to the real results. The proposed semantic analysis also requires documentation of the tool used, whether it is open-source software, a Python package, or a commercial platform.

The study is limited to literature related to computer science and artificial intelligence. Therefore, its results should not be directly generalized to medical or social fields without modifying the quality criteria. Studies published after the final search date should also be added before submission, especially in a rapidly developing field such as generative artificial intelligence.

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