




Systematic reviews in the era of artificial intelligence: Opportunities, challenges, and the future of evidence synthesis

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Abstract—Systematic reviews remain the cornerstone of evidence-based practice, providing a rigorous and transparent synthesis of research findings across diverse disciplines. However, the exponential growth of scientific literature has placed considerable pressure on traditional review methodologies, which are increasingly constrained by time, resources, and human capacity. In response, artificial intelligence (AI) has emerged as a transformative force in evidence synthesis, offering new opportunities to enhance the efficiency, accuracy, and scalability of systematic reviews. This article critically examines the integration of AI into the systematic review process, with particular attention to its applications across key stages, including literature searching, screening, data extraction, quality appraisal, and evidence synthesis. It further explores the benefits of AI, such as reduced workload, improved consistency, and accelerated review timelines, while also addressing important limitations, including algorithmic bias, lack of transparency, reproducibility concerns, and ethical challenges. In addition, the article considers the evolving roles of researchers and academic journals in adapting to AI-driven methodologies, emphasising the need for new competencies, reporting standards, and editorial guidelines. The article concludes that the future of systematic reviews lies in a hybrid model in which human expertise and artificial intelligence collaborate to strengthen the rigor, responsiveness, and impact of evidence synthesis in the digital age.

Keywords: AI-driven, Artificial intelligence, Evidence synthesis, Integration of AI, Systematic reviews

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I. INTRODUCTION

THIS inaugural article positions the *International Journal of Studies in Systematic Reviews* at the forefront of this transformation. Systematic reviews are widely recognised as the gold standard for synthesising evidence across fields such as the health sciences, education, psychology, and the social sciences, because their methodological rigor ensures transparency, reproducibility, and reliability in decision-making. However, the exponential increase in published research presents a major challenge. Thousands of articles are published daily, making it nearly impossible for researchers to manually identify, screen, and synthesise all relevant studies within a reasonable timeframe. The emergence of artificial intelligence (AI), particularly machine learning and natural language processing, offers new opportunities to address these challenges. As a result, AI technologies have the potential to revolutionise systematic reviews by automating repetitive tasks, enhancing accuracy, and enabling real-time evidence synthesis.

Role of AI in systematic reviews

It is increasingly important to consider the role of AI technologies in evidence synthesis for systematic reviews. Scholars indicated that AI encompasses a broad spectrum of computational techniques, including machine learning, deep learning, and natural language processing, which enable systems to perform tasks that typically require human cognitive abilities (Bolaños et al., 2024). In the context of systematic reviews, these technologies are progressively being integrated to enhance the efficiency, accuracy, and scalability of evidence synthesis processes (Ge et al., 2024; Sousa et al., 2026).

However, AI-driven tools are now applied across multiple stages of the systematic review workflow. During the initial phases, AI can assist

in refining research questions and developing comprehensive search strategies by identifying relevant keywords, synonyms, and semantic relationships within the literature. Similarly, some scholars demonstrated that in a study selection phase, machine learning algorithms are widely used to automate the screening of titles and abstracts, thereby significantly reducing the manual effort required to identify eligible studies (O'Mara-Eves et al., 2015; Clark et al., 2025).

Furthermore, AI technologies facilitate automated data extraction by identifying and capturing relevant variables from full-text articles. Other studies showed that the natural language processing techniques are critical because they enable the summarisation of study findings, allowing for rapid synthesis of large volumes of information (Bolaños et al., 2024). Similarly, Ge et al. (2024) highlighted that AI is also increasingly used to assess methodological quality and risk of bias, although human oversight remains essential to ensure validity and contextual accuracy.

In addition, AI supports advanced analytical processes, including meta-analysis and evidence mapping, by organising and structuring complex datasets. For example, AI-powered tools can generate structured search queries and identify relevant studies more efficiently than traditional manual approaches (Sousa et al., 2026). Moreover, large language models have demonstrated the capacity to assist in drafting sections of systematic reviews, including summaries of findings and discussion narratives (Clark et al., 2025). Despite these advancements, integrating AI into systematic reviews should be approached with caution, ensuring that automation complements rather than replaces critical human judgment and methodological oversight.

Evolution of systematic reviews

It is essential to note that the methodology of systematic reviews has evolved considerably over the past several decades, reflecting broader developments in research practices, methodological rigor, and

technological innovation. However, literature advocated that these advancements have enhanced the reliability, transparency, and overall utility of systematic reviews, firmly establishing them as a cornerstone of evidence-based practice across disciplines (Chandler et al., 2019; Moher et al., 2009).

In their early stages, systematic reviews were conducted entirely by hand, a process that was both time-consuming and prone to human error. Researchers relied heavily on hand-searching physical journal collections and bibliographies to identify relevant studies, often constrained by limited access to resources and incomplete indexing systems. Data extraction was similarly manual, requiring careful reading and recording of study characteristics and findings. Evidence synthesis during this period was predominantly narrative, with limited application of quantitative techniques. Consequently, early systematic reviews often lacked standardisation and were sometimes subject to interpretive bias due to the absence of structured, transparent methodologies (Chandler et al., 2019).

The introduction of standardised methodological frameworks marked a significant turning point in the evolution of systematic reviews. Guidelines such as PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) established clear criteria for reporting, thereby enhancing transparency and reproducibility (Moher et al., 2009). Similarly, the Cochrane Collaboration developed comprehensive methodological guidance for conducting systematic reviews, particularly in health research (Higgins et al., 2022). In parallel, the adoption of meta-analytic statistical techniques enabled researchers to quantitatively synthesise findings across studies, improving the precision and reliability of conclusions. These advancements contributed to greater methodological consistency and strengthened the credibility of systematic reviews as a robust scientific method.

The advent of digital technologies further revolutionised systematic reviews by improving access to scientific literature and analytical tools. Online databases such as PubMed and Scopus enabled researchers to conduct comprehensive and efficient literature searches across vast collections of academic publications (Gusenbauer & Haddaway, 2020). In addition, reference management software streamlined the organisation and citation of sources, while advanced statistical software facilitated more sophisticated meta-analyses.

Despite these technological advancements, the core processes of systematic reviews, such as study screening, data extraction, and critical appraisal, remain labour-intensive and time-consuming. This persistent challenge has laid the foundation for integrating emerging technologies, particularly artificial intelligence, to transform further and enhance evidence synthesis (Bolaños et al., 2024; Ge et al., 2024).

AI in systematic reviews

According to Gupta (2025), AI refers to computational systems designed to perform tasks that typically require human cognitive abilities, including learning, reasoning, pattern recognition, and language processing. In research contexts, AI enables the automation and augmentation of complex analytical processes, thereby enhancing efficiency and scalability (Bolaños et al., 2024; Ge et al., 2024).

Within systematic reviews, AI is primarily operationalised through several key technologies. Machine learning algorithms are used to identify patterns in data and make predictive decisions, particularly in study selection and classification tasks. Natural language processing facilitates the interpretation and analysis of textual data, enabling the extraction and summarisation of information from scientific literature. Additionally, deep learning techniques, a subset of machine learning, leverage neural networks to model complex relationships within large datasets, further enhancing AI systems' capacity to support evidence synthesis (Clark et al., 2025). Together, these technologies form the foundation of AI-assisted systematic reviews, enabling researchers to manage the growing volume of literature while maintaining methodological rigor (Sousa et al., 2026).

AI technologies are increasingly integrated across all stages of the systematic review process, from literature search to final reporting.

Their application not only improves efficiency but also has the potential to enhance the quality and consistency of reviews (Ge et al., 2024). AI significantly enhances literature search strategies by moving beyond traditional keyword-based approaches. Through semantic analysis, AI systems can interpret the contextual meaning of search terms, allowing for more comprehensive and accurate retrieval of relevant studies. Specifically, AI improves search processes by identifying synonyms and related concepts through semantic mapping, understanding contextual relationships within research questions, increasing recall (identifying all relevant studies), and improving precision (excluding irrelevant results). These capabilities enable more robust and efficient literature searches, reducing the risk of missing critical evidence (Bolaños et al., 2024).

One of the most impactful applications of AI in systematic reviews is in the screening and selection of studies. Machine learning classifiers can be trained on a subset of labeled data to distinguish relevant from irrelevant studies, thereby prioritising articles for inclusion. These systems can rank studies by relevance, reduce the volume of articles requiring manual screening, and maintain high sensitivity while significantly reducing reviewer workload (Sousa et al., 2026). It is important to note that AI-assisted screening tools such as Rayyan and ASReview illustrate the growing adoption of machine learning in evidence synthesis workflows. These tools support semi-automated screening while preserving human oversight. Data extraction is another area where AI, particularly natural language processing, demonstrates significant potential. AI systems can automatically identify and extract key information from full-text articles, including study characteristics (design, setting, and population), sample sizes, participant demographics, outcomes, interventions, and effect sizes. By automating these processes, AI reduces the likelihood of human error and accelerates the overall review timeline (Ge et al., 2024). However, the complexity and variability of reporting across studies make human validation essential.

It is important to note that systematic reviews are inherently susceptible to bias. AI applications for risk of bias assessment are emerging but remain less mature than other stages of the review process. AI systems are being developed to detect methodological limitations in study design, identify potential sources of bias such as selection bias and reporting bias, and support reviewers in critical appraisal tasks (Clark et al., 2025). Despite these advancements, fully automated bias assessment remains limited by the nuanced, context-dependent nature of methodological evaluation. Human expertise remains indispensable in ensuring accurate and reliable assessments. AI also plays an increasingly important role in the synthesis and reporting of evidence. Advanced algorithms and large language models can assist in summarising key findings across multiple studies, generating structured narratives for results and discussion sections, and supporting meta-analytic calculations by organizing and processing complex datasets (Bolaños et al., 2024). These capabilities facilitate more efficient reporting while maintaining coherence and structure. Nonetheless, careful oversight is required to ensure that AI-generated outputs are accurate, unbiased, and aligned with the underlying evidence.

Opportunities presented by AI

The integration of AI into systematic reviews presents a range of transformative opportunities that address longstanding limitations of traditional evidence synthesis. These opportunities extend across efficiency, scalability, consistency, and the evolution of dynamic review models (Ge et al., 2024; Sousa et al., 2026).

One of the most significant advantages of AI is its ability to reduce the time required to complete systematic reviews substantially. Traditional reviews often take several months or even years due to the labour-intensive nature of tasks such as literature screening, data extraction, and synthesis. AI-powered tools can automate many of these processes, enabling researchers to complete reviews within weeks. This acceleration is particularly valuable in rapidly evolving fields, such as public health and clinical research, where timely access to evidence is

critical for decision-making (Bolaños et al., 2024; Clark et al., 2025).

AI enhances the scalability of systematic reviews by enabling researchers to manage and analyse large volumes of data that would be impractical to process manually. Specifically, AI systems can efficiently handle extensive datasets drawn from multiple databases, thousands of publications across diverse disciplines, and multidisciplinary and heterogeneous evidence sources. This capability is essential in the current era of information overload, where the volume of published research continues to grow exponentially (Sousa et al., 2026). AI-driven scalability ensures that systematic reviews remain comprehensive and inclusive of relevant evidence.

AI also improves consistency and reliability in systematic reviews by standardising repetitive processes. Automated systems apply predefined criteria uniformly, reducing variability that may arise from human judgment. As a result, AI helps to minimise errors associated with human fatigue during large-scale screening, inconsistencies in study selection across multiple reviewers, and subjective bias in applying inclusion and exclusion criteria (Ge et al., 2024). By enhancing procedural consistency, AI strengthens the methodological rigor and reproducibility of systematic reviews. Nevertheless, human oversight remains essential to interpret complex or ambiguous cases.

Furthermore, AI plays a pivotal role in enabling the development of “living systematic reviews,” which are continuously updated as new evidence becomes available. Unlike traditional static reviews, living reviews incorporate new data in real time, ensuring that findings remain current and relevant. This approach supports real-time evidence synthesis for timely decision-making and fosters dynamic, continuously evolving knowledge systems (Clark et al., 2025). The ability to maintain up-to-date reviews is particularly important in fast-moving research areas, where outdated evidence can lead to suboptimal or even harmful decisions. AI-driven automation is, therefore, a key enabler of more responsive and adaptive evidence synthesis frameworks.

Challenges and limitations

Despite the considerable promise of AI for transforming systematic reviews, its integration into evidence synthesis poses several critical challenges and limitations. These concerns highlight the need for cautious and responsible adoption, ensuring that technological advancements do not compromise methodological rigor or ethical standards (Bolaños et al., 2024; Ge et al., 2024).

AI systems are inherently dependent on the data used to train them, making them susceptible to algorithmic bias. If training datasets are incomplete, unrepresentative, or skewed toward certain populations or disciplines, AI models may replicate and even amplify these biases. In systematic reviews, this can lead to the unintentional exclusion of relevant studies, particularly those from underrepresented regions or non-English publications, and to the overrepresentation of certain types of evidence. Such distortions may ultimately reinforce existing inequalities in global research visibility and knowledge production (Treviño & Arias-Carrión, 2025; Clark et al., 2025). Addressing algorithmic bias, therefore, requires careful dataset curation, inclusive data practices, and continuous validation of AI outputs.

A major limitation of many AI systems, particularly those based on deep learning, is their lack of transparency. These systems often operate as “black boxes,” with internal decision-making processes that are difficult for users to interpret. This poses significant challenges for systematic reviews, which rely on transparency and reproducibility as core principles. Specifically, the opacity of AI systems can make it difficult to understand how studies are selected or excluded, limit the ability to justify methodological decisions, and ultimately undermine trust in AI-assisted review processes (Bolaños et al., 2024). Although advances in explainable AI are beginning to address these concerns, their widespread implementation remains limited.

Reproducibility is a fundamental requirement of systematic reviews; however, the use of AI introduces new complexities that make it more difficult to maintain consistent and replicable results. Variations in algorithm design and configuration, training datasets, data

preprocessing methods, and software tools or platform updates can lead to differences in outputs across studies or over time. This variability challenges the standardisation of AI-assisted reviews and complicates efforts to replicate findings (Sousa et al., 2026). Ensuring reproducibility, therefore, requires comprehensive documentation of AI methodologies, version control, and adherence to standardised reporting practices.

The integration of AI into systematic reviews also raises several important ethical issues that must be carefully considered. Key concerns include authorship and intellectual contribution, particularly in determining the appropriate recognition of AI-assisted outputs in academic work; data privacy and security, especially in ensuring that sensitive or proprietary data used in AI systems are adequately protected; and accountability, given the lack of clarity regarding responsibility for errors or inaccuracies in AI-generated outputs (Clark et al., 2025). These ethical considerations underscore the importance of establishing clear guidelines, governance frameworks, and regulatory standards for the responsible use of AI in research.

Role of human expertise in AI-assisted systematic reviews

Despite the rapid advancement of AI in evidence synthesis, human expertise remains indispensable to the integrity and credibility of systematic reviews. While AI technologies can automate and accelerate many technical processes, they lack the nuanced judgment, contextual awareness, and ethical reasoning required for high-quality research (Bolaños et al., 2024; Clark et al., 2025). Human researchers play a critical role in providing critical thinking and interpretation, enabling the evaluation of complex and sometimes conflicting evidence.

Human expertise also encompasses contextual understanding, which ensures that findings are interpreted within appropriate theoretical, cultural, and disciplinary frameworks. In addition, ethical judgment is essential in guiding responsible decision-making in areas such as study inclusion, data use, and reporting (Ge et al., 2024). Methodological oversight further ensures adherence to established standards and frameworks, thereby maintaining the rigor and transparency of the review process (Sousa et al., 2026).

Importantly, systematic reviews often involve subjective decisions such as interpreting ambiguous findings, assessing study quality, or resolving disagreements that cannot be fully automated. AI systems, while powerful, operate based on patterns in data and predefined algorithms, and therefore lack the capacity for reflective judgment, contextual sensitivity, and accountability (Treviño & Arias-Carrión, 2025). Consequently, a hybrid model that combines AI-driven efficiency with human expertise is widely regarded as the most effective and responsible approach (Clark et al., 2025). In this model, AI is used to manage repetitive, data-intensive tasks, such as literature screening and data extraction, while human researchers retain control over critical decision-making processes. This collaborative framework not only enhances productivity but also preserves the methodological rigor, transparency, and ethical standards essential to systematic reviews. Ultimately, the future of evidence synthesis depends not on replacing human researchers but on augmenting their capabilities through the thoughtful integration of AI technologies.

II. IMPLICATIONS FOR JOURNALS AND RESEARCHERS

The integration of AI into systematic reviews carries significant implications for both researchers and academic journals. These implications extend beyond methodological adjustments to include capacity building, ethical governance, and the evolution of publication standards in evidence synthesis.

Researchers

For researchers, adopting artificial intelligence (AI) in systematic reviews requires developing new competencies and methodological approaches. As AI tools become increasingly embedded in research workflows, scholars are expected to engage with these technologies both critically and effectively (Bolaños et al., 2024; Sousa et al., 2026). This article highlights several key implications, including the need for training in AI tools and methodologies. Researchers must acquire

practical skills in using AI-driven platforms for literature searching, screening, data extraction, and synthesis. A clear understanding of the capabilities and limitations of these tools is essential for their responsible and effective application (Ge et al., 2024).

Furthermore, integrating AI into systematic reviews requires adopting interdisciplinary approaches. Effective implementation often requires collaboration among domain experts, data scientists, statisticians, and information specialists. Such interdisciplinary engagement enhances methodological rigor, promotes innovation, and ensures the appropriate interpretation of AI-generated outputs (Clark et al., 2025). In addition, this article emphasises the importance of developing digital literacy skills. Researchers must cultivate strong digital competencies, including familiarity with machine learning concepts, natural language processing applications, and data management practices. These skills are increasingly indispensable for conducting high-quality, AI-assisted systematic reviews and for critically appraising automated outputs (Treviño & Arias-Carrión, 2025). Collectively, these competencies enable researchers to critically evaluate AI-generated results and ensure that technological advancements align with established principles of scientific rigor, transparency, and reproducibility.

Journals

Academic journals play a crucial role in shaping the standards and expectations surrounding the use of AI in research. As AI becomes more prevalent in systematic reviews, journals must adapt their policies and editorial practices to ensure transparency, accountability, and methodological integrity (Bolaños et al., 2024; Clark et al., 2025). This article indicates that researchers must assume critical responsibilities in the appropriate use of AI; however, journal editors also play a central governance role. Editors must establish clear guidelines for AI-assisted research, explicitly outlining acceptable uses of AI in systematic reviews and specifying requirements for disclosure and methodological reporting (Ge et al., 2024).

Furthermore, journal editors must ensure transparency in reporting AI use by requiring authors to provide clearly documented accounts of how AI tools were applied throughout the review process. This includes detailed descriptions of the software, algorithms, and application stages, thereby supporting reproducibility and methodological clarity (Treviño & Arias-Carrión, 2025). In addition, editorial processes must evolve to accommodate AI-assisted research. This involves adapting peer-review systems and equipping reviewers with the guidance and training needed to critically evaluate AI-integrated manuscripts, particularly regarding methodological validity, bias, and reproducibility (Dokaliuk et al., 2025).

In this context, journals such as the *International Journal of Studies in Systematic Reviews* are well-positioned to provide leadership in the field. They can contribute by promoting methodological innovation in evidence synthesis, establishing and disseminating standards for AI integration, and encouraging the responsible and ethical use of AI in systematic reviews. By taking an active role in shaping these developments, journals can ensure that AI enhances rather than undermines the quality, transparency, and credibility of scholarly evidence synthesis.

Future directions

The future of systematic reviews is expected to be profoundly shaped by continued advancements in AI, data science, and digital research infrastructure. As these technologies mature, evidence synthesis is likely to become more automated, interconnected, and dynamically responsive to emerging research. Recent methodological research highlights that AI-assisted systematic reviews are already improving efficiency in screening and study selection, although full automation remains limited due to the continued need for human oversight and methodological judgment (Bolaños et al., 2024; Clark et al., 2025).

One anticipated development is the emergence of semi- to fully automated review pipelines, where AI systems support multiple stages of the systematic review process, including literature search, screening,

data extraction, and preliminary synthesis. AI-based tools have already demonstrated measurable reductions in workload during title and abstract screening while maintaining high sensitivity in identifying relevant studies (Gates et al., 2020). However, full automation remains unlikely in the near term due to the complexity of interpretive tasks and the necessity of human critical appraisal (Treviño & Arias-Carrión, 2025). Another important direction is the integration of systematic reviews with big data ecosystems and open science platforms. This integration will allow researchers to access real-time datasets, preprints, clinical trial registries, and open-access repositories, thereby enhancing the comprehensiveness and timeliness of evidence synthesis. Initiatives in open science have been shown to improve transparency, reproducibility, and data accessibility, particularly when combined with AI-enabled retrieval systems (UNESCO, 2021; Wilkinson et al., 2016). Such connectivity also supports greater transparency and reproducibility in research practices.

The development of standardised AI tools and methodological protocols is also expected to play a critical role in the future landscape. Standardisation will help address current challenges in AI-assisted reviews, including variability in outputs, reproducibility concerns, and transparency limitations (Page et al., 2021). It will also facilitate broader adoption of AI technologies across disciplines by providing clear operational guidelines and reporting standards for AI-assisted systematic reviews.

In addition, the future of systematic reviews will be characterised by enhanced collaboration between humans and machines, in which AI systems serve as intelligent assistants rather than autonomous decision-makers. Evidence suggests that hybrid human-AI models outperform fully automated systems in maintaining both efficiency and methodological validity, particularly in complex evidence synthesis tasks (O'Mara-Eves et al., 2013; Clark et al., 2025). This collaborative model will optimise efficiency while preserving the essential role of human expertise in interpretation, ethical judgment, and methodological oversight.

Emerging technologies such as generative AI and knowledge graphs are also poised to transform evidence synthesis. Generative AI models have demonstrated the ability to assist in drafting research narratives, summarising findings, and generating preliminary interpretations of evidence (Bender et al., 2021; Clark et al., 2025). Meanwhile, knowledge graphs enable the mapping of relationships among studies, interventions, outcomes, and concepts, thereby supporting more structured, semantically richer evidence synthesis (Hogan et al., 2021). Together, these innovations will enable more interconnected, adaptive, and intelligent approaches to synthesising evidence.

Overall, the future of systematic reviews lies in the convergence of intelligent technologies and human expertise, leading to faster, more comprehensive, and more dynamic systems for generating and disseminating evidence.

III. CONCLUSION

AI represents a significant paradigm shift in the methodology of systematic reviews and the broader field of evidence synthesis. Its integration into research workflows has fundamentally transformed how literature is searched, screened, analysed, and synthesised, offering unprecedented gains in efficiency, scalability, and consistency. These advancements enable researchers to manage increasingly large and complex bodies of evidence in ways previously not feasible with traditional manual approaches. However, alongside these benefits, AI also introduces important methodological, ethical, and epistemological challenges. Concerns related to algorithmic bias, transparency, reproducibility, and accountability highlight the limitations of current AI systems in fully replacing human judgment. In particular, the "black box" nature of many AI models raises questions about interpretability and trust, which are central to the credibility of systematic reviews. Given these complexities, the future of systematic reviews does not lie in replacing human researchers but rather in integrating AI technologies

with human expertise. A hybrid model in which AI supports repetitive, data-intensive tasks while humans retain responsibility for critical interpretation, ethical decision-making, and methodological oversight offers the most balanced and sustainable approach. By embracing technological innovation while maintaining rigorous scientific standards, the research community can ensure that systematic reviews remain robust, transparent, and trustworthy. In this way, AI will not diminish the role of systematic reviews but will instead enhance their relevance and impact in the rapidly evolving digital and information-rich era.

IV. CONFLICTS OF INTEREST

There are no conflicts of interest in this study.

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