

AUTOMATING THE SYSTEMATIC LITERATURE REVIEW PROCESS IN MANAGEMENT SCIENCE USING ARTIFICIAL INTELLIGENCE

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DOI: 10.2478/minib-2025-0007

ABSTRACT

Systematic literature reviews (SLR) are essential for synthesizing research across disciplines, yet their manual execution is time-consuming and increasingly challenging due to the rapid proliferation of academic publications. This study examines the role of artificial intelligence (AI) in the SLR process within management sciences. Drawing on established SLR methodologies, particularly from health sciences where automation is widely applied, this research identifies AI's role in contributing to key review stages, including literature identification, selection, data extraction, synthesis, and reporting. This study itself applied a systematic literature review methodology, querying Scopus and Web of Science, complemented by AI-based tools (Elicit and SciSpace) to extend coverage. Backward and forward citation searches were also conducted, resulting in a final sample of 93 publications. The findings from this sample suggest that AI enables researchers to shift roles from literature examiners to managers of the review process, overseeing AI tools executing repetitive and time-consuming tasks. However, despite the benefits of using AI in generating SLRs, its application in management research presents challenges, particularly in handling context-dependent and interpretative analyses. The study highlights both the transformative potential and the critical need for human oversight in AI-assisted reviews. Limitations include the reliance on existing automation techniques developed for health sciences and the exclusion of certain literature sources. Future research should explore AI's effectiveness in managing SLRs, ethical considerations, and hybrid human–AI collaboration models. AI's growing role in academic research entails the need to balance automation with scholarly rigor and methodological integrity.

Key words: systematic literature review, artificial intelligence, management, process management, academic writing, ChatGPT.

Type of the work: review article

Article History

Received: July 29, 2025 | Revised: September 20, 2025 | Accepted: October 09, 2025

1. Introduction

Systematic literature reviews (SLR) shape scholarship in many disciplines, functioning as a rigorous method for synthesizing existing primary research. They are particularly important in fields such as the health sciences and management, where the proliferation of publications entails a need for more effective and dependable methods to condense vast bodies of information into practical insights (Tantawy et al., 2023; Tsafnat et al., 2013, 2014; Tranfield et al., 2003). The introduction of artificial intelligence (AI) into the SLR process promises to transform and greatly enhance its efficiency and accuracy through automation – especially in repetitive and time-consuming tasks, such as data extraction and synthesis (Clark et al., 2020; Lau, 2019).

The use of AI in SLRs represents more than just a technological advancement; it signifies a shift in the researcher's role from a traditional examiner of literature to a manager of research processes. In process management, the manager plans, organizes, coordinates, and controls the work (Sommerville et al., 2010), whereas the employees execute the assigned tasks. Transferring this logic to the process of creating a systematic literature review, the researcher, acting as manager, can plan that process, organize the work, coordinate the use of AI applications, and monitor their effects on the outcomes. The AI algorithms carry out the instructions provided by the manager. The whole process remains grounded in the established methodological logic of systematic literature reviews (see Denyer & Tranfield, 2009; Vrontis & Christofi, 2021).

This shift brings both new opportunities and challenges that are redefining the academic research landscape (Vrontis & Christofi, 2021; Wagner et al., 2022). AI tools can quickly become collaborative partners, enabling complex analyses that extend beyond simple automation, even supporting the generation of novel research questions and hypotheses (Saeidnia et al., 2024).

In this paper, we consider the role of AI in the SLR process. AI functions as a collaborator, with the potential to redefine the researcher's role. Based on a systematic review of the relevant literature, this study explores how AI is currently utilized in SLRs and proposes a framework for future collaboration between humans and AI in academic writing and research. These practical and philosophical considerations highlight the evolving relationship between human researchers and AI technologies.

With the advancement of AI technologies, traditional ideas of authorship and the researcher's role in knowledge creation are increasingly being challenged. AI can not only support the research process but also autonomously carry out certain tasks, raising questions about maintaining integrity and accountability in scientific output (Howard, 2024; Masukume, 2024).

This article also discusses the variability and difficulties associated with incorporating AI into management-focused systematic reviews, where the nuanced and contextual aspects of research may pose challenges for automation. The goal is to present a balanced perspective that acknowledges both the potential of AI to improve research methods and the need for researchers to ensure that AI applications align with academic standards and ethical considerations.

Building on this foundation, we formulated the following research question: How can AI support the SLR process in management? This question itself was then addressed through a systematic literature review.

This study adopts a transdisciplinary approach to research methodology, integrating perspectives from management, information science, and technology studies. By exploring how artificial intelligence can be meaningfully embedded in the process of conducting systematic literature reviews, the article addresses not only academic concerns but also the practical needs of external stakeholders – including research institutions, consulting firms, and organizations seeking evidence-based insights. The proposed human–AI collaboration framework encourages more inclusive and participatory models of knowledge creation, potentially involving non-academic actors in the innovation process by enabling faster and more accessible synthesis of research findings. In doing so, the paper aligns with broader efforts to make academic inquiry more responsive, collaborative, and relevant to real-world challenges in business and society.

2. Research design

Data collection

We conducted searches using commonly accepted search algorithms in the Scopus and Web of Science databases, which contain the largest collections of peer-reviewed academic publications (Glińska & Siemieniako, 2018, Paul & Criado, 2020). We formulated two search queries (one for each database) corresponding to the most common keywords of our basic research concepts, and we followed the database protocols regarding the use of Boolean operators AND, OR, and appropriate truncations (*).

1. ("Automation" OR "Automating" OR "Automated" OR "Automatic" OR "Automates" OR "Mining")
2. ("Systematic review*" OR "Systematic Literature Review*")
3. ("Artificial intelligence" OR "AI")

This yielded the following query for Scopus, which returned 1,297 studies:

TITLE-ABS-KEY(("Automation" OR "Automating" OR "Automated" OR "Automatic" OR "Automates" OR "Mining") AND ("Systematic review*" OR "Systematic Literature Review*") AND ("Artificial intelligence" OR "AI")).

On Web of Science, we used the following query, which returned 785 studies:

TS = (("Automation" OR "Automating" OR "Automated" OR "Automatic" OR "Automates" OR "Mining") AND ("Systematic review*" OR "Systematic Literature Review*") AND ("Artificial intelligence" OR "AI")).

Together, both queries produced an initial sample of 2,082 studies.

Data selection

Three inclusion criteria were applied to select which articles to review. Papers had to be scientific in nature, published in peer-reviewed scientific journals, and written in English. This reduced the initial sample to 1,649 papers. Next, two exclusion criteria were introduced during title and abstract screening. We excluded papers that merely mentioned AI automation in SLRs without describing its application, as well as studies focusing solely on specific phases of the SLR process rather than automation or AI in general. These were mainly technical articles not including any broader context or concept. We also eliminated duplicates from the two databases.

Following this exclusion process, 34 publications remained. Then we added four articles found through AI engines (Elicit and SciSpace software). We then conducted a backward citation search analysis on these 38 articles, yielding 17 additional papers (for a total of 55 in all). Finally, we performed a one-layer forward citation search, which produced 38 additional articles, proceedings, preprints and one doctoral thesis. The final sample consisted of 93 publications, collected as of April 8, 2024.

We chose not to conduct a formal quality assessment due to the emerging nature of the topic. At this nascent stage of the research field, we deemed it more valuable to analyse all available sources to ensure comprehensive coverage.

Figure 1 presents the sample selection procedure.

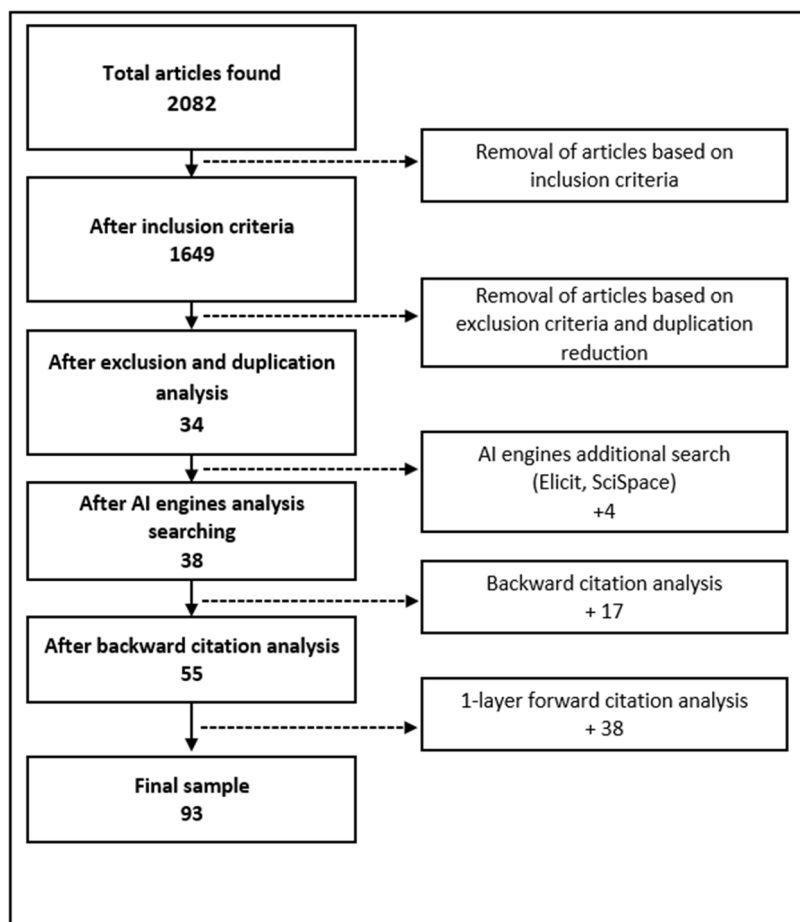


Figure 1. Literature search protocol.

The final set of 93 publications was analysed using thematic analysis. We coded the material to identify recurring themes related to the integration of AI into the SLR process. The themes were grouped according to the stages of the review process. The findings were then synthesized to build a framework supporting researchers' collaboration with AI in academic writing. Based on our analysis of 93 studies, we identified how AI contributes to different stages of the SLR process. The review revealed that AI tools are used in scoping, research question formulation, literature identification and selection, data extraction, synthesis, and reporting. These findings of our analysis form the basis for the human researcher–AI collaboration framework we propose.

3. Results

Systematic literature review as a form of scientific writing in management

A *systematic literature review* (SLR) is a rigorous method for identifying, selecting, evaluating, analysing, and synthesizing existing research findings on a specific topic. It follows a precisely defined and replicable procedure for systematically gathering knowledge on a given topic. The results are transparent and can be verified by other researchers (van Dinter et al., 2021). In contrast to traditional literature reviews used in empirical articles, SLRs employ detailed criteria for selecting and evaluating the quality of source articles and the possibility of using the results in different contexts. They are used to identify research gaps, develop new ideas, and generate comprehensive reviews of the state of the art in specific research fields (Denyer & Tranfield, 2009).

Automation of the SLR process has so far been most widely implemented in the health sciences (Laynor, 2022; Tsafnat et al., 2013, 2014). This trend is reflected in our findings, as more than 70% of the articles in our sample are from that domain. Systematic literature reviews in the health sciences are a comprehensive and scientifically rigorous approach to summarizing existing evidence on a specific topic. As volume of research publications continues to increase, SLRs help researchers, healthcare providers, and medical practitioners stay informed about the latest evidence and practices (Laynor, 2022).

SLRs in management sciences, although no less important than in health sciences, are nevertheless considerably less developed. There therefore remains an under-satisfied need for rigorous synthesis of research findings in the field (Siemieniako et al., 2022), providing a comprehensive and relatively unbiased analysis of the existing literature on particular topics in management. SLRs help identify research gaps, inform directions for future research, and reduce the time spent synthesizing existing sources (Denyer & Tranfield, 2009). Scholars have advocated for the use of systematic review methods in management and organizational studies to advance evidence-based management practices (Tranfield et al., 2003). While certain adjustments may be expected in traditional systematic review methodologies to accommodate the unique characteristics of the management field, the benefits of using systematic literature reviews are widely recognized (Tranfield et al., 2003).

Given the significant progress achieved in automating SLRs within the health sciences and their growing importance in management, it is worth exploring how similar automation could be implemented in this context. To address our research question, the following section presents the various phases of SLRs in management sciences and examines the current possibilities of their automation, based on practices in the health sciences.

Systematic literature review phases in management

As outlined by Tranfield et al. (2003) and Denyer and Tranfield (2009), the general phases of a systematic literature review in management typically include:

Planning the review: The researcher plans the review and defines the scope, protocol, and process for conducting the literature review. In this step, the researcher considers which databases and tools to use, what skills are needed, how to allocate time, and how to search for high-quality resources.

Conducting the search: Next the researcher collects and selects primary studies that are relevant to the review topic. The researcher performs database searches, screens the citations, assesses the quality of the studies, extracts data, and monitors the activities.

Analyzing & synthesizing the literature: In the next phase, the researcher correlates the evidence from multiple sources, synthesizes results, and then arranges the data in order to address the research questions.

Reporting the findings: This final stage involves preparing and disseminating the review results. This includes formatting the main report, reviewing the report, summarizing the findings, discussing limitations, formulating recommendations for policy and practice, and identifying future research areas.

For this study, we adopted the concise and clear procedure developed by Vrontis and Christofi (2021), which also corresponds to the process outlined by Denyer and Tranfield (2009). This procedure consists of the following steps.

Conducting a scoping review: Scoping analysis defines the boundaries and focus of a research study, systematically determining which studies to include according to established criteria and the timeframe to be covered (Vrontis & Christofi, 2021). The main aim is to develop a comprehensive, structured review of relevant literature. This analysis facilitates mapping the field; identifying the main trends, gaps, and opportunities for theoretical development; and providing solid and reliable evidence for further research. A scoping analysis, therefore, allows researchers to efficiently and effectively assemble, assess, and collate the available literature to inform study objectives and methodologies (Vrontis & Christofi, 2021).

Identifying the research purpose and research question: In the next step, the researcher identifies the research purpose and research question by defining the scope and the focus of the study. This process follows a comprehensive scoping review, which enhances awareness of gaps, trends, and what is already known on the subject of interest (Pereira et al., 2023). Finally, research questions are formulated based on this preliminary study to meet the review's overall research objectives.

One effective way to formulate a research question is through the interplay between the researchers and feedback from experts in academia and from the relevant industries

(Vrontis & Christofi, 2021). Such an iterative process may better focus the research question so as to better capture the intent. The research question should be grounded in an understanding of the interface between different variables or concepts under study (Billore et al., 2023).

At this stage, it is also important to consider the inclusion criteria, regarding what the study will seek to address and what kinds of sources to include (Vrontis & Christofi, 2021). Well-honed inclusion criteria ensure that a research question remains focused and relevant to the set research objectives. Generally, by following a structured methodology, researchers can formulate well-defined research questions in line with the overall research aim.

Identifying the research context: The research context is the particular setting, condition, or background in which the study takes place. It incorporates the industry under study, participants' cultural traits, geographical locations, time periods, and all those elements which may have an effect on the research topic or its findings (Vrontis et al., 2020).

Understanding the research context is therefore crucial for interpreting and generalizing findings, since different contexts may lead researchers to varying outcomes with different implications (Christofi et al., 2017). Researchers usually design their studies with contextual factors in mind to ensure that their findings are relevant and applicable in particular situations (Baima et al., 2020). By examining different research contexts, scholars can gain new insights, refine theories, and enhance their understanding of a particular area of study (Vrontis et al., 2022).

Identifying the literature: Literature identification is a systematic process of searching for, selecting, and analysing relevant publications and research studies with respect to a given topic or issue. This typically includes assessing the relevance and quality of the literature found and synthesizing key findings into insights about the current state of knowledge on the subject under investigation. Identifying the literature allows researchers to better grasp the theoretical approaches taken and the extant research gaps, trends, and challenges in the respective field of study. In other words, this step enables scholars to map out the current state of the subject and, consequently, to identify gaps and trends in order to support the development of scientific projects (Jain et al., 2022).

Selecting the literature: In the fifth step, the relevant sources of information – such as research articles, books, and other publications – are selected for inclusion in the study or review. This process requires the setting of clear selection criteria, such as the studies' research questions, objectives, and the quality of the sources. These criteria help to identify and screen potential sources and, finally, select relevant and high-quality literature to be further studied (Christofi et al., 2017). The systematic methodologies used in conducting literature reviews help researchers ensure a very rigorous and comprehensive selection process for this step of the review (Battisti et al., 2023). Through careful selection,

researcher build a solid foundation of existing knowledge and findings relevant to their own study.

Extracting and synthesizing data: Data extraction involves the systematic collection of relevant data from the selected articles or research papers, according to predefined criteria. This includes identifying and recording specific information such as publication details, author details, article type, methods used, key findings, and other relevant data points (Christofi et al., 2021). Data synthesis, by contrast, involves analysing the extracted material to identify patterns, relationships, or common themes in the literature. This stage aims at synthesizing the data from the different sources of information into a coherent framework or model that will then guide further research or provide practical implications (Christofi et al., 2021). This is then followed by thematic analysis to integrate the results into an overall framework, further enabling in-depth understanding of interrelating concepts (Battisti et al., 2023). In general, data synthesis facilitates the generation of meaningful inferences from the literature review and provides directions for future research.

Reporting and making recommendations: This final stage involves preparing the report and recommendations, which requires summarizing and synthesizing the results of the reviewed studies in a structured and transparent manner. Principal results, themes, and lessons learned from the literature are organized and presented comprehensively. The authors of the review identify gaps in the literature, propose future directions, and offer recommendations for both academics and practitioners based on their analysis of the reviewed studies. The ultimate aim is to contribute valuable insights to the existing knowledge base of the research area and guide further research efforts (Christofi et al., 2017; Pereira et al., 2023).

Automation of SLRs in management

In this section, we illustrate how artificial intelligence tools can be used to automate specific stages of the systematic literature review process. The examples come mainly from health sciences literature, but the same SLR procedures are increasingly being used in management (Denyer & Tranfield, 2009).

Scientific automation refers to the application of technological instruments and procedures to mechanize and enhance a number of scientific processes related to data collection, analysis, and reporting. Within the context of systematic reviews, it entails the use of software and algorithms to accelerate the review process and to efficiently and accurately synthesize evidence (Lau, 2019). The tasks that can be automated for systematic reviews include literature screening, data extraction, and meta-analysis (Tóth et al., 2023). More generally, science automation aims to improve efficiency, transparency, and

reproducibility, while reducing costs by taking advantage of better technology and artificial intelligence (Laynor, 2022).

Scoping analysis

AI algorithms can help automate several tasks within scoping analysis, facilitating the extraction of key information from large bodies of scientific literature – such as author names, affiliations, keywords, citation counts, or topics (Saeidnia et al., 2024). By analysing citation networks, AI systems can identify highly cited and influential papers and reveal the dynamics of scientific knowledge diffusion. They may also predict the potential impact of scientific research based on a variety of factors. Moreover, they may detect and visualize research collaborations through co-authorship networks and publication histories. Applying natural language processing (NLP) techniques can make it easier for researchers to identify emerging trends and topics during the scoping analysis (Saeidnia et al., 2024).

Identifying the research purpose and research questions

AI can assist researchers in posing research questions by providing data-driven insights and optimized methodologies. It can identify gaps in the available literature, generate hypotheses, and even predict probable correlations or causal relationships. AI tools can, therefore, enhance the brainstorming process with insights drawn from existing trends, historical data, and cross-disciplinary studies that may ultimately set researchers onto new investigative paths (Wagner et al., 2022). Moreover, given AI's advanced capacity to analyse data faster and more accurately than is humanly possible, it can reveal hidden patterns, correlations, and emerging research trends that enable the researcher to find new directions to pursue (Saeidnia et al., 2024; Tomczyk et al., 2024).

However, while AI can significantly increase the efficiency of the research process, human judgment and critical thinking remain indispensable for determining which research gaps merit exploration and how they should be addressed (Spillias et al., 2023). While AI can open up ways to fast-track the process of identifying relevant literature and proposing hypotheses, human judgment is necessary for generating meaningful questions through problematization (Wagner et al., 2022).

Identifying the research context

AI can also contribute to defining research contexts by generating ideas, reviewing the literature, analysing data, and mapping out collaboration networks (Saeidnia et al., 2024). AI algorithms are able to process large amounts of data to pinpoint underexplored areas within a field (Khalifa & Albadawy, 2024). In this respect, using natural language processing techniques, AI can extract keywords, topics, and trends from scientific

publications that may be helpful for the research community to find new directions and emerging areas of focus in the respective domains (Saeidnia et al., 2024). Moreover, AI can contribute to the generation of ideas and hypotheses and to the development of robust designs by proposing relevant research problems as well as methodologies (Khalifa & Albadawy, 2024). It can be applied to predict emerging research trends; identify potential collaborators and influential research networks, and measure the impact and visibility of scientific papers, authors, and journals (Saeidnia et al., 2024).

Identifying literature

AI techniques can identify relevant literature in various ways. Algorithms can distinguish between authors with similar names by considering variables such as institutional affiliations and publication histories (Saeidnia et al., 2024). This guarantees that scholarly work is attributed correctly and also enhances the reliability of bibliometric analysis.

Researchers are increasingly applying AI techniques such as machine learning (ML) and data mining in bibliometrics in order to predict future publication trends, emerging research areas, and research impact (Saeidnia et al., 2024). AI algorithms can recognize patterns and relationships in large bibliographic datasets, and then deliver critical insights regarding what the scientific enterprise of research may look like in the years to come. Such studies may significantly enhance researchers' capacity to recognize and remain abreast of key trends and research collaborations.

As Saeidnia et al. (2024) observed, AI algorithms can automatically collect bibliographic data from a variety of sources, such as online databases, academic libraries, and digital repositories, and this may save a lot of time and effort for researchers engaged in data collection. AI analysis of citation networks also helps locate influential papers, authors, and journals, highlighting the impact and visibility of research outputs and spotting key trends.

Selecting literature

AI can facilitate the literature-selection stage through advanced methods for knowledge representation and inference, text manipulation, and learning from large amounts of data. These techniques are particularly useful for tasks that are laborious or repetitive for humans, such as the critical analysis of scientific literature (de la Torre-López et al., 2023). AI tools support the clear specification of problem domains and literature-selection criteria, thus enabling researchers to apply search and selection criteria, save time, and ensure transparency and quality in the literature review (Ngwenyama & Rowe, 2024). AI-based tools can potentially deal with fuzzy, weakly structured, and unstructured

data, providing abstraction and semantic meaning-based analysis that can support searching and screening tasks for literature selection (Wagner et al., 2022). Advanced supervised machine learning methods, such as deep learning (DL), are used to automate decisions on the relevance of papers. This alleviates researchers from the tedious task of rule-codification and also makes the literature-selection processes more efficient (Wagner et al., 2022). Essentially, AI tools offer capabilities that can be harnessed to advance the effectiveness, efficiency, and accuracy of the literature-selection processes, thus proving very instrumental for researchers in their quest to navigate the veritable sea of literature available in many domains.

Extracting and synthesizing data

In the data-extraction phase, AI tools can automatically extract information from articles, whether structured through elements of the PICO framework or specific data points, using ML/DL/NLP methods (Santos et al., 2023). AI tools can assist in summarizing and interpreting the extracted information in formats that will enable graphic and statistical synthesis, including the generation of tables, diagrams, and graphs examining between-study heterogeneity, and in updating meta-analyses and related forest plots (Amezcu-Prieto et al., 2020). These capabilities of AI thus support faster data-extraction and synthesis processes in literature reviews, improving efficiency and quality in synthesizing evidence in scholarly research.

Reporting and preparing recommendations

AI-driven tools can contribute significantly to improved manuscript preparation, assisting in such stages as grammar correction, text rewriting, and recommendation generation – often tailored to the users' individual preferences and writing style (Chemaya & Martin, 2023). AI systems can also automatically identify missing data, synthesize evidence from source studies, and identify topics through automated text clustering (Santos et al., 2023). Moreover, AI algorithms can digest large numbers of scientific publications to retrieve information about author names, affiliations, keywords, or citations, all of which may help researchers gain a better grasp the publication patterns, underlying research networks, and collaborations in a scientific area (Saeidnia et al., 2024).

AI-powered recommender systems can be used to recommend relevant scientific websites, online resources, and research collaborations based on user preferences, reading behaviour, and web data (Saeidnia et al., 2024). Natural language processing and machine learning techniques may play a central role in these systems, supporting the analysis of web-based documents, extraction of key information, understanding of research outputs, and assessment of impact and visibility of online scientific research (Saeidnia et al., 2024).

The reviewed literature shows that AI capabilities in data extraction, analysis, and recommendation generation are transforming the process of reporting, explaining, and communicating research findings – bringing a revolution in how academic and research outputs are reported and shared. Table 1 presents a summary of this analysis.

Table 1. AI capabilities across different stages of the systematic literature review (SLR) process.

SLR step	Role of AI	Sources
Scoping analysis	Automates extraction of key information such as author names, affiliations, keywords, citation counts, and topics from research publications; analyzes citation networks to identify influential papers, predicts research impact, and identifies collaborations.	Saeidnia et al., 2024
Research purpose and research questions	Identifies gaps in the literature, generates hypotheses, predicts correlations and causal relationships, and provides insights from existing trends and cross-disciplinary studies to help set new research directions.	Wagner et al., 2022; Saeidnia et al., 2024
Research context identification	Processes large datasets to identify literature gaps, extract keywords, topics, and trends; generates ideas, hypotheses, and research problems; predicts emerging trends; detects potential collaborators; and measures impact and visibility.	Saeidnia et al., 2024; Khalifa & Albadawy, 2024
Literature identification	Disambiguates authors; predicts publication trends and research impact; automatically collects bibliographic data; analyzes citation networks to identify influential papers, authors, and journals.	Saeidnia et al., 2024
Literature selection	Provides efficient methods for text manipulation, knowledge representation, and inference; uses machine learning to automate decisions on the relevance of papers, supporting efficient and accurate literature-selection processes.	de la Torre-López et al., 2023; Ngwenyama & Rowe, 2024; Wagner et al., 2022
Data extraction and synthesis	Automatically extracts information from articles using ML/DL/NLP methods, summarizes extracted data, creates tables and graphs, updates meta-analyses, and synthesizes data to create structured tables and diagrams summarizing evidence.	Santos et al., 2023; Amezcua-Prieto et al., 2020

Reporting and recommendations preparation	Assists in grammar correction, text rewriting, recommendation generation, automatic identification of missing data, evidence synthesis, topic identification, and recommending relevant resources and collaborations based on user preferences.	Chemaya & Martin, 2023; Santos et al., 2023; Saeidnia et al., 2024
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In summary, this section has demonstrated how artificial intelligence can support the automation of the various phases of systematic literature reviews, which therefore answers our core research question. More specifically, we investigated how AI applications implemented in the SLR procedures for health sciences can be applied to management sciences. The SLR procedure adopted here follows the framework proposed by Vrontis and Christofi (2021), who extended that of Denyer and Tranfield (2009).

4. Conclusions, Limitations, and Future Research

The integration of artificial intelligence into systematic literature reviews represents not merely an evolution, but a revolution – one that challenges the very foundation of academic research. The traditional painstaking process of identifying, analysing, and synthesizing literature is being rapidly overtaken by AI-driven automation, fundamentally shifting the researcher’s role from that of an intellectual labourer to that of a process manager.

To further illustrate the balance between human oversight and machine capability, this transformation can be productively examined in terms of the data–prediction–judgment–action model (Agrawal, Gans, & Goldfarb, 2018). According to this model, AI improves the prediction stage by processing large amounts of information, whereas the stages of judgment and action remain the responsibility of humans. Applied to SLRs, this implies that researchers are not passive supervisors. Rather, they must critically evaluate AI outputs, interpret them, and decide how to integrate them into existing theory. AI can automate the identification of literature and point to potential gaps, yet it cannot replace human judgment in assessing relevance or drawing conclusions. A useful analogy can be found in the military domain, where AI improves predictive capacities but decision-making authority ultimately remains with humans (Agrawal, Gans, & Goldfarb, 2018). This framework thus reinforces our view that AI does not eliminate the researcher’s role. Instead, it redefines it. Researchers remain managers of the process, with their judgment and action ensuring rigor and depth.

However, this transformation is not universally welcomed. While it may lead to improved efficiency, scalability, and precision, one must ask: At what cost? Increased

reliance on AI threatens to erode the depth of critical engagement with literature, potentially reducing researchers to mere supervisors of algorithms rather than active participants in knowledge creation. Yet AI systems are not neutral; they inherit the biases of their training data, the priorities of their programmers, and the constraints of their algorithms. If left unchecked, these embedded biases could reshape academic discourse in ways we are only beginning to understand.

The present study has a number of limitations, which reflect broader concerns about AI's role in research. The fact that most extant SLR automation techniques stem from health sciences raises a crucial question: Is management research even compatible with such mechanization? The field of management thrives on context, interpretation, and theoretical nuance – elements that AI, for all its computational power, struggles to grapple with. Applying automation techniques designed for medical trials to a discipline that values qualitative insight may, at best, be an oversimplification and, at worst, an intellectual misstep. Moreover, our reliance on peer-reviewed studies from established databases inadvertently sidelines alternative perspectives and cutting-edge discussions happening outside traditional academic publishing. If AI is trained only on what is deemed “acceptable” by established gatekeepers, are we not reinforcing the very same academic silos that researchers have long criticized? The omission of formal quality assessment further highlights the immaturity of this research area. We have embraced AI before rigorously questioning whether it genuinely improves the research process – or simply accelerates flawed methodologies.

As far as further limitations are concerned, the number of references included in this study could possibly have been larger, but it was the direct outcome of our systematic selection procedure. The final set of publications was determined through predefined keywords and strict inclusion and exclusion criteria, ensuring objectivity and transparency. As a result, the number of sources may have been smaller than expected, but it accurately reflects the available and relevant research within the scope of this emerging field.

The fact that our own study was itself conducted through the systematic literature review method also invites some brief reflection on this process. We relied on established databases (Scopus and Web of Science) and complemented them with AI-based tools such as Elicit and SciSpace to identify additional sources. While this approach provided a broad coverage of relevant studies, it also revealed challenges that are characteristic of AI-assisted reviews. For example, integrating results from traditional databases and AI tools required additional effort to ensure consistency and avoid duplication. Furthermore, while AI engines accelerated the retrieval of relevant articles, they sometimes produced results lacking sufficient context or theoretical framing, which required careful human judgment. These experiences confirm our broader argument: AI can support the prediction and data

retrieval stages, but the stages of judgment and action remain dependent on researchers. By reflecting on our own process, we emphasise the importance of methodological transparency and show that the opportunities and limitations of AI-assisted SLRs are not only conceptual but also practical realities encountered during research.

Looking ahead, future research must confront these uncomfortable realities rather than blindly celebrate AI's capabilities. Instead of merely asking how AI can make SLRs more efficient, we should ask whether AI-assisted reviews do actually produce better knowledge at all. If AI is allowed to dictate research agendas by prioritizing what is most frequently cited, we risk creating an academic echo chamber where innovation is stifled in favour of algorithmic consensus.

The ethical implications are equally alarming. Who takes responsibility when AI-generated literature reviews misrepresent findings or reinforce biases? The obsession with automation must be tempered with a serious conversation about accountability and intellectual integrity. Scholars must resist the temptation to let AI do their thinking for them. The most pressing challenge is not improving AI but ensuring that human researchers remain the architects of inquiry rather than its passive facilitators. The future of AI-driven research is not inevitable – it is a choice. Whether that choice leads to a new era of intellectual empowerment or a hollowing out of academic rigor depends entirely on how critically we engage with this technology now.

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