Transformative Automation: AI in Scientific Literature Reviews

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***Abstract*—This paper investigates the integration of Artificial Intelligence (AI) into systematic literature reviews (SLRs), aiming to address the challenges associated with the manual review process. SLRs, a crucial aspect of scholarly research, often prove time-consuming and prone to errors. In response, this work explores the application of AI techniques, including Natural Language Processing (NLP), machine learning, data mining, and text analytics, to automate various stages of the SLR process. Specifically, we focus on paper identification, information extraction, and data synthesis. The study delves into the roles of NLP and machine learning algorithms in automating the identification of relevant papers based on defined criteria. Researchers now have access to a diverse set of AI-based tools and platforms designed to streamline SLRs, offering automated search, retrieval, text mining, and analysis of relevant publications. The dynamic field of AI-driven SLR automation continues to evolve, with ongoing exploration of new techniques and enhancements to existing algorithms. This shift from manual efforts to automation not only enhances the efficiency and effectiveness of SLRs but also marks a significant advancement in the broader research process.**

***Keywords*—Artificial intelligence; systematic literature review; scholarly data analysis; machine learning algorithms; natural language processing; scientific publication automation**

I. Introduction

Artificial intelligence (AI) has emerged to alleviate humans from repetitive tasks that demand specific human skills. Like any other field, scientific endeavors benefit from powerful algorithms to expedite and enhance outcomes. Initiating a new research project typically involves a thorough investigation of relevant scholarly publications to comprehend the landscape and identify activities significant for addressing similar or related issues. The process of gathering documents, when performed without prior training or well-defined parameters, may lead to the omission of significant contributions [29]. A comprehensive approach to searching and analyzing literature can help reduce the likelihood of bias and inaccuracy in research [24], [28].

A systematic literature review (SLR) is a secondary investigation that assesses existing research, employing a widely recognized procedure to identify related articles, extract pertinent details, and present their main findings in an organized manner [33]. It is anticipated that a published literature review will deliver a comprehensive summary of a corresponding research subject, often providing a historical perspective that facilitates the identification of research trends and unresolved issues. Literature reviews are now a fundamental component of many scientific fields, including medicine (with 13,510 published reviews) and computer science (with 6,342) [47].

Conducting a literature review is known to be time-consuming, especially when addressing a vast research subject. In recent years, various systematic literature review (SLR)-related tools have been developed for diverse purposes [47]. These tools can automate digital database searches, designate relevant outcomes based on inclusion criteria, and provide visual support for analyzing information from works' authors and their citations, among other capabilities. Particularly, the automation of the SLR process is gaining attention in the field of computer science research, offering strategies to construct search phrases and retrieve publications semi-automatically or manually from relevant scientific databases [76]. The utilization of automated methods has proven to save time and costs in selecting relevant articles [11], or providing a summary of the findings [71]. However, some authors argue that the usefulness of these automated tools is limited by their steep learning curve and the lack of research analyzing the advantages they offer [74].

This paper focuses on the computerized and automated operation of SLR tasks, replacing manual labor with ML as the primary driver. The goal is to enhance the capability of automated review processes and technologies with some additional understanding and suggestions. The initial application of AI methods to automate SLR tasks occurred in 2006 [12], where it was suggested that neural networks could be used to automate the selection of relevant articles. Initial resistance to this idea stemmed from concerns regarding the use of data gleaned from secondary sources through text mining [51].

Following this concept, previous works by other researchers have delved into powerful text mining techniques [52], [58], [65]. Recent innovations in the field include the integration of ML and natural language processing (NLP) techniques [27], [76]. Considering the repetitive tasks involved in a SLR methodology, the capabilities of AI for analyzing scientific literature are vast. However, it's crucial not to devalue the role of human involvement in this process, as humans bring a holistic perspective that current AI techniques may lack.

An exciting development in the field of SLR is the relatively recent introduction of AI tools for automating the entire procedure — a field anticipated to continue expanding in the coming years. The increasing curiosity level indicates that now is an opportune time to analyze AI techniques presented as solutions to various SLR tasks. This analysis includes a focus on their intended use, sources of input and output, and the need for human intervention. Several research efforts in the field have incorporated AI techniques into their evaluations of procedures and instruments for facilitating SLR tasks. However, these investigations have taken either a more general approach, considering any type of automation with or without AI, or they have exclusively focused on AI [47], [76]. Some experts have concentrated on the use of specific AI techniques, such as ML methods, to address a particular problem [49] or a specific SLR activity, like document selection [57], [58].

Despite these efforts, some investigations may lack a comprehensive overview of the diverse ideas and procedures involved in AI relevant to the entire SLR procedure. In addition to providing a comprehensive overview of the field, the present paper aims to expand on the significance of human involvement—a perspective not fully addressed by the partially autonomous SLR considered in the existing literature reviews. Keeping these goals in mind, the following are a few inquiry concerns, also known as Research Questions (RQs), that inform our analysis of the current status of AI-based SLR automation:

- RQ1: Which stages of the SLR process have been automated using artificial intelligence?
- RQ2: Which AI methods facilitate the automation of SLR tasks?
- RQ3: To what extent does the human factor into SLR automation with AI?

As part of our survey, we conducted a systematic literature search to address the above RQs. We identified the latest original research articles from an extensive collection of references retrieved through both mechanical and human search systems. Reviewing these articles was essential to comprehend the motivation behind employing AI for specific tasks. We then scrutinized the inputs, outputs, and algorithmic choices of the proposed methods, along with information on the experimental evaluation of the approaches, including benchmarking metrics and sample articles.

Our analysis revealed that certain SLR tasks have been the subject of significantly more research compared to others, with some ML approaches introduced in the early phases still in use. However, we also identified more recent studies investigating novel ML approaches that incorporate the human dimension. Our findings in response to each RQ allowed us to pinpoint several unresolved concerns and difficulties related to the use of AI techniques for SLR tasks that they were not specifically designed for. Additionally, we identified issues related to experimental repeatability and other factors that have not yet been thoroughly addressed.

The remainder of this paper is organized as follows: Section II provides an overview of related work, highlighting existing literature and studies pertinent to the integration of AI in systematic literature reviews. In Section III, we delve into the methodology employed in our research, elucidating the approach and techniques used. Section IV explores the landscape of AI-based support for the literature review process, detailing advancements, tools, and strategies. Following this, Section V outlines open issues and challenges associated with AI-driven literature reviews. Section VI offers conclusions drawn from our exploration and proposes avenues for future research. These sections collectively contribute to a comprehensive understanding of the current state and potential future developments in the intersection of AI and systematic literature reviews.

II. Related Work

A systematic examination of existing research, known as a Systematic Literature Review (SLR), is a type of secondary investigation in a research field that systematically combines and evaluates scientific research to synthesize recent information, critically discuss current initiatives, and detect research patterns. SLRs use established procedures for conducting empirical research [33]. In particular, within Software Engineering (SE), researchers have made efforts to provide a comprehensive summary of methods devised for automating the SLR procedure. With a methodical approach to searching, they have reviewed the literature to shed light on different approaches used to automate various aspects of the SLR process [20].

In this context, our focus shifts to the work presented in [19], which demonstrates how computer languages can facilitate unsupervised ML for the synthesis and abstraction of data sets taken from an SLR. This article skillfully showcases the complementary roles that AI and ML techniques play in coding, categorization, and synthesis of SLR data, utilizing the qualitative method Deductive Qualitative Analysis [5].

While SLRs offer a clear and concise format for summarizing expertise in a field, they are not without challenges, such as the time required to complete them and the challenging task of assessing the integrity of primary research [35]. Recent analysis has highlighted prevalent hazards associated with SLR replication, emphasizing issues resulting from the absence of a defined methodology [38]. The approach [33] divides the SLR procedure into the following stages:

1) Formulating phase: The first aspect involves making a strategy. Justification for conducting an SLR in a research area ensures it addresses a gap and contributes to knowledge. Research queries are formulated to define the purview of the SLR and guide its evolution. These queries may adhere to predetermined structures, such as PICO (Population, Intervention, Comparison, and Outcome) or SPICE (Context, Perspective, Intervention, Comparison, and Evaluation) [15]. In this stage, an evaluation procedure is designed, including a comprehensive review technique applicable to each stage. The search technique and its sources, such as science resources and journals, are detailed in the protocol. Eligibility requirements for article selection, data extraction, and quality evaluation guidelines are also established.

2) Conducting phase: The second phase involves the execution of autonomous searches in data and digital libraries.

Search strings are obtained from either the formulated research queries or constructed using a supplementary method [50]. Additional sources, including dark texts and snowballs, are considered [42]. The former includes materials not publicly available, such as dissertations and presentations. The snowball effect involves discovering new literary works by examining references and citations from previously discovered papers. Relevant studies are identified by removing duplicates, evaluating candidates based on the name and summary, and applying inclusion and exclusion criteria. These criteria specify the quality standards each article must meet to be included in the scope [60]. The fundamental subjects are then analyzed to extract data, and summary statistics are obtained to synthesize and visualize the collected data.

3) Reporting phase: The third phase focuses on the reporting process and the evaluation of the final report's completeness and quality. Authors determine the manner in which the material is discussed and presented, as well as whether the evaluation result is suitable for publication. Criteria are considered to evaluate whether necessary data can be found in the SLR report [44].

III. Methodology

A. Search Strategy

The search strategy employs a combination of automated and human searching methods. Automated searches were conducted using the following sources: ACM Library, IEEE Xplore, Scopus, SpringerLink, and Web of Science. The search criteria, designed to retrieve publications, include a range of terms incorporating systematic review keywords and automation-related terms. General terms associated with automation were used rather than an exhaustive list of specific AI methods for two distinct purposes: (1) to avoid skewing the findings in favor of certain methods, ensuring inclusion of less prevalent ways in the final tally; and (2) to prevent the creation of lengthy and complicated search strings that may be challenging for databases to process. Title, keywords, and abstracts were considered in the search criteria. The resulting search string was easily adaptable for each data source. Additionally, a manual search was conducted using reverse snowballing. After reviewing the titles and abstracts of the initial eight candidate papers, six were added to the final list.

Fifty prospective papers were identified and underwent further evaluation to ensure their alignment with our research aims. For this purpose, both exclusion and inclusion criteria were developed. Papers written in languages other than English, those with unavailable full content, and publications lacking a demonstrated peer review process were excluded. The inclusion criteria set specific requirements for paper content. Each research paper must focus on automating multiple steps of an SLR and discuss the usage of AI-based methods for inclusion in the current survey. This general criterion is further subdivided into mutually exclusive options:

1) The paper explains a novel algorithm, instrument, or method facilitating full or partial mechanization of SLR;
2) It provides an examination of the relevance of AI in SLR, along with a critique of the latest developments in this field of study; and
3) The paper presents a summary of SLR tools applicable to one or more phases.

B. Data Extraction

Once each primary research article has been identified, data extraction is performed following the guidelines outlined in [33]. One author reviews each article, with the assistance of a second reviewer in cases of ambiguity. The data extraction form includes meta-information such as authors and affiliations, research types, publication years, and publishing years.

The data extraction form also includes categories to define the AI approach followed in each paper. Specifically, each paper's content is summarized based on the following criteria:

1) Phase and aim of the SLR: Each paper is classified according to the phase of SLR automation, and each phase's categorization is followed by a description of the particular step(s) involved in that phase.

2) AI domain and technique: The paper is assigned to one or multiple automated academic subfields and contains a concise explanation of the employed algorithm or technique. We also record whether the societal factor is at play.

3) Experimental framework: Types of primary research include empirical, theoretical, application, and review. We compile the body of data and the indicators used for performance evaluation for empirical investigations.

4) Repeatability: Changes are made if any of the supplied tools, datasets, or algorithms require them. We verify the accessibility of any websites or repositories cited as supplementary material to ensure repeatability.

IV. AI-based Support for the Literature Review Process

A literature review process often involves some visionary and mechanical constraints, prompting the development of AI-based technologies to alleviate the workload for potential authors. AI technologies aim to handle time-consuming and repetitive tasks, allowing authors to focus on interpretation, intuitive leaps, and skills [72].

To provide readers with insight into the current state of knowledge in this domain, we systematically evaluate each stage of the literature review process, highlighting existing AI-based tools and discussing the potential for further AI assistance. The following agenda can outline opportunities for additional industrial development and enhancement [69].

Table I presents a concise overview, indicating whether each stage is capable of being assisted by AI and guiding the reader toward relevant tools. The term "melted brief" refers to a succinct summary, capturing the essence of each stage's AI-assistive potential.

In particular, we conducted a comprehensive review of relevant literature on AI-based tools, consulting sources such as [1], [21], [26], [37]. Given the dynamic nature of AI technologies and the rapid evolution of AI tools, we focused

TABLE I. AI-BASED TOOLS FOR STEPS IN THE REVIEW PROCESS

Steps	AI-based Tools	Potential for AI-support
1. Problem Formulation	1) Resources for software development supporting thematic analyses based on LDA models [3]. 2) GUI applications and programming libraries supporting scientometric analyses [67].	1) Moderate potential with AI potentially pointing researchers to promising areas and questions or verifying research gaps.
2. Literature Search	1) TheoryOn enables ontology-based searches for constructs and construct relationships in behavioral theories [43]. 2) Litbaskets supports researchers in setting a manageable breadth in regard to the magazines that have been covered [9]. 3) LitSonar allows syntax interpretation of queries between database servers, as well as (journal coverage) creating reports [66].	1) Very high potential since the most important search methods consist of steps that are repetitive and time-consuming, that is, amenable to automation.
3. Screening for Inclusion	1) ASReview offers screening prioritization [75]. 2) ADIT approach for researchers capable of designing and programming ML classifiers [40].	1) A significant opportunity for partly automated assistance in the initial stage screen, which requires many repetitive decisions. 2) Substantial possibility of an extra screen, requiring substantial expert judgement (particularly for ambiguous cases).
4. Quality Assessment	1) Statistical software packages (e.g., RevMan). 2) RobotReviewer for experimental research [48].	1) There is a possibility for partially automated quality control ranging from low to considerable.
5. Data Extraction	1) Software for data extraction and qualitative content analysis (e.g., Nvivo and ATLAS.ti) offers AI-based functionality for qualitative coding, named entity recognition, and sentiment analysis. 2) WebPlotDigitizer and Graph2Data for extracting data from statistical plots.	1) Moderate potential for reviews requiring formal data extraction (descriptive reviews, scoping reviews, meta-analyses, and qualitative systematic reviews). 2) Elevated for quantitative and discrete data points (e.g., sample sizes), low for detailed information that is ambiguous and open to multiple interpretations (e.g., theorizing and main results).
6. Data Analysis and Interpretation	1) Descriptive synthesis Tools for text-mining [36], scientometric techniques, topic models [55], [63], and computational reviews aimed at stimulating conceptual contributions [4]. 2) Theory building: Examples of inductive (computationally intensive) theory development [8], [45], [56]. 3) Tools for doing meta-analyses, such as RevMan and dmetar, are used in the testing of hypotheses.	1) Very high potential for descriptive syntheses. 2) Moderate potential for (inductive) theory development and theory testing. 3) Low non-existent potential for reviews adopting traditional and interpretive approaches.

our evaluation on those most pertinent to our primary objective in the realm of Information Systems (IS) research. It is also important to note that our review is not exhaustive; rather, its purpose is to spotlight potential examples that can benefit IS researchers. In the upcoming paragraphs, we take a focused approach, examining AI-supported tasks individually. This approach allows us to provide insights into tools that authors can seamlessly integrate into a comprehensive data processing and toolchain.

A. Step 1: Problem Formulation

In the initial phase of a comprehensive literature research, authors bear the responsibility of not only defining and elucidating research topics but also elucidating the fundamental ideas and theories within the relevant field [69]. Furthermore, scholars are advised to conduct a preliminary assessment of the research gap, determining whether the gap has been adequately addressed. Evaluating if the study's issue offers an opportunity for a substantial contribution that surpasses previous works and determining its significance in filling the existing void are crucial considerations in this phase [54], [62].

We envisage that AI can significantly contribute to the synthesis of research issues, particularly in the phase focused on identifying and validating open questions. With substantial advancements in the scientific domain, researchers have made significant strides in pinpointing gaps in the current body of knowledge and formulating plausible hypotheses. In this context, we anticipate that social science researchers can leverage and adapt these findings to enhance their own work. For instance, revolutionary developments in automated hypothesis generation and experimental testing have emerged in biochemistry, particularly within fully automated labs [34]. Additionally, ML strategies have been employed in scientometric approaches, facilitating literature-based discoveries in computer science [70]. These advancements underscore the potential for AI to play a transformative role in issue synthesis across various scientific disciplines.

Significant strides in information technology, particularly in the realm of database inquiries, have garnered attention. Three noteworthy resources underscore these recent advancements. Notably, TheoryOn's search engine [43] stands out. While these advancements hold promise, especially for studies in the social sciences, their ultimate influence on research methodologies remains to be seen. In general, these technological developments may prompt investigators to identify areas warranting further exploration or additional research. However, we acknowledge that, for problematization-driven research that generates queries, a continued reliance on deliberative democracy, particularly in the phase of problem identification, may be necessary [2].

In addition to recognizing voids within existing studies and areas calling for extensive exploration, AI holds the potential to assist researchers in assessing whether these gaps persist by locating prior assessments with similar or identical content. However, it's important to acknowledge that utilizing AI in this context may introduce a degree of unpredictability during the phases of discovery and verification, particularly when identifying prior assessments with content resembling the current study.

In conclusion, the support for this pioneering initiative in AI-backed research is still in its infancy, marked by a limited number of documented approaches. Notably, the existing software operates autonomously, diverging from the reliance on established graphical user interface tools. For researchers proficient in programming, inspiration can be drawn from exploring the intersections of various literature or study areas. This exploration opens avenues for cross-disciplinary research and identifies areas where further investigation is warranted. To facilitate this exploration, researchers can leverage scientometric approaches and enhance their development [18], [67]. Additionally, employing tools such as the LDA subject model can contribute to the identification of potential research directions [3]. As the field evolves, there is significant room for growth, and researchers are encouraged to embrace the interdisciplinary nature of AI-backed research to unlock its full potential.

B. Step 2: Literature Search

In this stage, researchers embark on constructing a comprehensive corpus of published works utilizing a diverse set of search techniques, including database queries, perusal of table of contents, citation inquiries, and additional searches [69]. The objective of the literature search can vary, with authors striving for either comprehensive, representative, or selective coverage based on the review's purpose [13].

Complex search strategies, involving multiple iterations and leveraging the collaboration with artificial intelligence-based technologies, are devised from corresponding search methods. Given the diverse nature of the knowledge retrieval process, encompassing various data sources such as journals, conference proceedings, books, and various forms of grey literature, alongside concerns about data quality, authors must employ appropriate data management strategies. These strategies should not only facilitate transparent reporting [61] but also contribute to repeatability and reproduction [14].

Recent advancements in information technology, particularly in the realm of database inquiries, have been noteworthy. Three notable resources stand out in this regard. Firstly, TheoryOn's search engine [43] enables researchers to conduct ontology-based inquiries for distinct elements and interactions between themes across different behavioral hypotheses. This offers an alternative to traditional databases and presents a more sophisticated approach to information retrieval. Secondly, Litbaskets [9] contributes to the development of search methodologies by remotely estimating the likely number of responses from a database search based on predefined phrases across various journals with editable entries. Thirdly, LitSonar [66] adds automation to the search process by translating search terms for multiple book systems, including databases like EBSCO Digital Library, AIS eLibrary, and Lexisnexis. This tool is particularly promising as it provides real-time updates on service availability, potentially identifying database prohibitions (periods during which articles are not searchable) and alleviating challenges associated with database deficiencies.

In a broader context, the literature search phase holds the potential for automation, addressing numerous technological tasks that researchers encounter. The expanding volume of research output, coupled with the imperative need for efficiency and accuracy, underscores the significance of incorporating robotics and AI assistance in activities that are predominantly mechanical in nature [10], [25]. The integration of these technologies not only expedites the literature search process but also mitigates the inefficient use of faculty time resulting from manual tasks. This becomes especially critical in an era marked by the rapid proliferation of scholarly content.

C. Step 3: Screening for Inclusion

In this pivotal phase of the literature review, the authors employ a systematic screening process to differentiate between relevant and irrelevant papers. Conventionally, this phase is bifurcated into a preliminary assessment based on titles and abstracts, followed by a more rigorous second screening based on full-texts [69].

Manual screening, involving the meticulous examination of hundreds or thousands of documents, can be mentally taxing, potentially hindering the accurate identification of challenging scenarios. To mitigate this challenge, researchers are advised to conduct an initial screening where obviously irrelevant articles (based on titles and abstracts) are excluded. Articles posing difficulty are intentionally saved for a more comprehensive evaluation in the second round of screening.

The second screening involves a smaller sample, allowing for efficient screening (after excluding the majority in the initial screen). This stage involves a thorough examination of materials, application of predefined stringent exclusion criteria, and simultaneous independent evaluations, with group decisions on borderline cases. The screening process, particularly in hypothesis-testing reviews, requires stringent scrutiny, as inclusion errors could significantly impact the study outcomes [69].

Over time, the landscape of screening tools has evolved with the incorporation of AI-based tools [21]. Among them, ASReview [75], a tool with minimal limitations, stands out as a promising option for IS researchers. Operating on health sciences databases and requiring PubMed IDs are not significant limitations for ASReview. This tool, developed recently, is noteworthy for its transparency (under the Apache-2.0 License), script accessibility (implemented in Python), and the ability to easily integrate new features. ASReview employs various ML classifiers, including Naive Bayes, logistic regression, Logical Regressive Analysis, and randomly generated forest classifiers. It leverages initial diversity decisions to enhance subsequent decision accuracy. Researchers receive a ranked catalog of papers (titles and descriptions), facilitating efficient processing of an ordered compilation. The tool even allows for automated exclusion after screening a specific number of papers consecutively, streamlining the screening process. Papers with borderline relevance can be deferred for later assessment, guided by their content [75].

For researchers with coding proficiency, customization of the discourse method is possible [40]. In situations where the evaluation of popular theories becomes impractical due to the sheer volume of pertinent documents, the prospect of randomly selecting theory-contributing publications is proposed. This approach leverages algorithms used in ML to identify a subset of relevant journals from the larger pool, thereby offering a randomized sample typical of how scientists articulate their work during literature reviews [40].

Anticipating the AI-support potential, the first screening demonstrates high efficacy, while the potential for the second screening is moderate. The initial screen, involving fewer exclusions, is more amenable to digitization and AI assistance. This presupposes computers with proficient reading and comprehension capabilities for brief descriptions and titles. Conversely, the subsequent screen deals with the remaining instances and may prove challenging due to the less standardized nature of IS research. Unlike fields like Medical and Biological Sciences, IS research lacks commonly used categories for constructs, standard keyword vocabulary (e.g., MeSH terms), and consistently descriptive paper titles, making effective classification challenging [58]. This challenge is not exclusive to machines and equally affects human reviewers.

Screening and search, treated as information retrieval tasks, should primarily be evaluated based on recall, representing the proportion of successfully retrieved relevant papers. Traditionally, literature reviews aimed for high recall, resulting in exhaustive searches, low precision, and increased screening burdens [43]. AI-supported ontology-based searches, such as those facilitated by ASReview, hold the promise of efficiently alleviating a portion of the screening load by increasing precision.

The screening processes remain among the most time-consuming aspects of a literature review process [10]. When considering the potential of AI assistance for these steps, it's crucial to recognize that the reliability of manual screening methods should not be overstated, as even screenings conducted by experts exhibit a disagreement rate of 10% on average [81]. Augmenting researchers' screening activities with AI tools can help identify inconsistent and potentially erroneous screening decisions, enhancing the reliability of the screening process.

D. Step 4: Quality Assessment

The evaluation of major empirical research for methodological flaws and potential sources of bias is an integral part of the quality assessment process [23], [33], [69]. This phase aims to gauge the extent to which the findings of evaluations, particularly those intended for theory testing, may be influenced by various types of bias, such as selection bias, mortality bias, and evaluation bias. Parallel and independent execution of these procedures is recommended to ensure high dependability [69].

The prospect of AI-based tools contributing to these processes is considered to have a low to middling chance for two primary reasons. Firstly, the task of judging the quality of a method is challenging, requiring expert opinion and often presenting difficulties in achieving high inter-coder agreement [22]. Secondly, IS reviews, whether quantitative or qualitative, typically involve manageable numbers of samples, making manual assessments feasible.

For researchers conducting meta-analyses and systematic literature searches, conventional tools like RevMan, adhering to standards for evaluating qualitative research methodology and risk of bias [7], or equivalent statistical application environments such as R and SPSS are commonly used. Additionally, AI-based applications like RobotReviewer [48] offer relevance to IS meta-analyses. RobotReviewer, focusing on risk of bias assessment in randomized controlled trials within the life sciences, serves as an exemplary instance of explainable AI. It enables scholars to trace ratings in each bias area back to their source within the full-text document. This transparency contributes to the reliability and interpretability of the bias assessment process.

E. Step 5: Data Extraction

The extraction of data, both qualitative and quantitative, involves the identification of relevant information and its categorization into a (semi) structured code sheet [69], [79]. This step is more prominent in description, scoping, and theory testing reports compared to narrative reviews and assessments of theoretical development, which tend to be more selective and interpretive. Commonly utilized software for all-encompassing subjective data analysis includes ATLAS.ti and NVivo, which are increasingly incorporating ML and NLP techniques. These techniques include methods for information extraction from data tables, automation of descriptive coding, Named Entity Recognition (NER), sentiment analysis, and analysis of statistical plots. Examples of tools for extracting data from statistical plots include WebPlotDigitizer and Graph2Data.

The potential for AI support in this step is anticipated to be moderate. Future advancements may focus on improving the efficiency of information extraction, highlighting crucial elements in an article, and facilitating the organization of information in suitable databases. However, complete automation of more intricate data elements is not expected in the near future. Despite the more standardized disclosure practices in the medical professions, tools for extracting features such as Population, Intervention, Comparison, and Outcome (PICO) criteria are still in their early stages of development [26].

F. Step 6: Data Analysis and Interpretation

The concluding stage of the evaluation process in literature reviews can take various forms depending on the type of assessment [69]. Some literature reviews emphasize intricate scenarios that provide insights and profound hermeneutic interpretations, while others aim to eliminate subjectivity that might compromise the reliability of summary statistics and generalizations.

IS researchers employ various instruments for data analysis, depending on the main objectives for knowledge development [64]. For comprehensive synthesis, several well-established techniques are available, including text-mining tools [36] and instruments that utilize scientometric, computational, or Latent Dirichlet Allocation (LDA) models to analyze and visualize themes, theories, and research communities [6], [17], [41], [55], [68], [70], [77], [78]. For example, text-mining tools can provide descriptive insights based on topic modeling, offering a promising approach to conceptual contributions [39], [53], [63]. In the realm of IS, meta-analysis programs and libraries, such as RevMan and the R package dmetar [7], are utilized for putting hypotheses to the test. Future AI-based technologies supporting data analysis should consider the diverse approaches available. While AI can efficiently ease certain aspects of descriptive evaluations through topic modeling, the creative and unstructured nature of theory development poses challenges for AI-led theory-building efforts [8], [45], [56].

The inductive method of IS theory development seems most amenable to AI assistance, although current examples in the behavioral research domain may not match the ingenuity and originality exhibited by exceptional theoretical and historical context articles [4], [39], [53], [63]. It is crucial to emphasize that AI's contribution to theory development lies not only in identifying connections but also in elucidating the "why" behind these connections and establishing fundamental philosophical foundations of justification [25], [82]. This aspect remains an unrestricted challenge for future theory advancement based on AI.

Fig. 1 illustrates the three layers of the SLR-centric approach, emphasizing the goals for research, design, and action within the Information Systems (IS) domain. This three-layered SLR-centric model within the IS domain underscores the interplay between infrastructure, methodologies/tools, and actual research practices, showcasing the integral components for successful literature reviews.

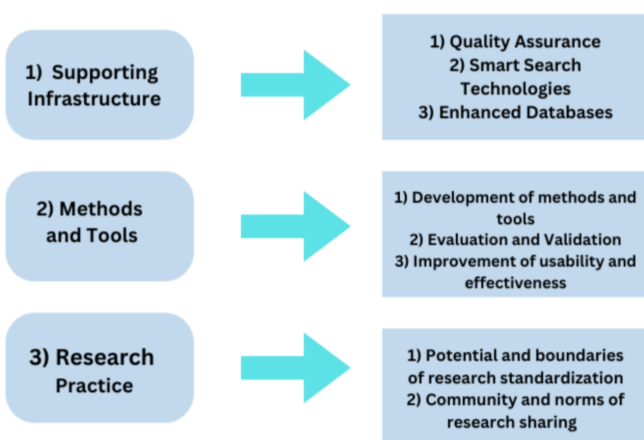

Fig. 1. SLR-Centric research, design, and action.

Quality assurance is integral to ensuring the accuracy, dependability, and consistency of data collected and analyzed during the literature review [23], [33], [69]. Smart technologies, incorporating automation and clever algorithms, enhance the efficiency and effectiveness of literature review operations [30], [31], [46], [59], [73], [80]. Improved databases are essential for efficiently storing, maintaining, and retrieving literature review data [14]. Integrating these features into the infrastructure supporting SLR substantially enhances the quality, efficiency, and insights of the review process.

The standardization debate in the realm of Information Systems (IS) revolves around whether standardized approaches, methodologies, and technology should be embraced across multiple IS applications or whether variety and flexibility should be prioritized [32]. The concept of sharing supplementary research outputs emphasizes the necessity of sharing not only traditional research publications but also other significant outputs contributing to the research process. This includes datasets, code, methodology, negative outcomes, and other relevant items [64].

V. Open Issues and Challenges

A. The Emphasis is Primarily on One Activity

Automating SLR processes using AI research is heavily skewed towards the execution of paper selection procedure, especially during the phase of paper assignment. While this activity is also time-consuming, it is important to note that applying AI to various tasks within the SLR process requires attention. Preliminary tasks, such as AI-driven writing activities (e.g., drafting research questions, specifying exclusion/inclusion criteria, and presenting SLR reports), are areas that need further development.

B. More Research Needs to Be Done on AI Methods

While there is a broad range of AI fields and techniques, certain ones have not yet been employed in SLR automation. Methods for optimization and inquiry, for instance, have not been thoroughly investigated as potential solutions for SLR-related tasks. These strategies, traditionally used to resolve planning issues, may find application in prioritizing resources during the initial stages, such as selecting the best databases or assigning papers to editors based on their skills. Compared to ML, knowledge representation and NLP are less frequent, and most proposals appear to be in early stages. Therefore, there is a need for more tools and frameworks to develop solutions based on these methods.

C. Additional Active Human Participation can Benefit Artificial Intelligence

The cooperation between humans and AI methods or instruments is currently limited in terms of scope and nature. Under an active learning strategy, the human role is primarily focused on providing labels for paper selection. However, the organizing and composing phases, which demand greater human capabilities, might benefit from engaging artificial intelligence. Involving people in this process could result in additional positive outcomes, such as tailoring the results to their preferences.

D. The Adoption of AI for SLR Automation can be Enhanced

Most current successful ideas are rooted in either the medical or technological domains, with specific domain taxonomies or concepts sometimes used to construct the list of capabilities. Full replicability of genuine systematic literature reviews is not always achieved, and the lack of benchmarks remains a significant obstacle. Evaluating AI techniques across a broader range of SLRs and expanding the scope of discussed issues requires additional development.

E. Users of SLR Automation may Lack Expertise in Artificial Intelligence

Many ML techniques examined thus far, such as support vector machines (SVM) and neural networks, which are commonly referred to as "black-box" techniques. The challenge arises from insufficient confidence in automated conclusions due to the participation of scientists from diverse disciplines in SLRs, who may not necessarily be experts in AI. There has been limited exploration of models using human-readable code, including simple decision trees and rule-based systems. Furthermore, the utilization of contemporary explainable techniques has the potential to enhance the outcomes of black-box artificial intelligence solutions developed in this field.

VI. Conclusions and Future Work

A. Conclusions

Literature reviews represent just one facet of a laborious and error-prone process that can be streamlined with the assistance of artificial intelligence (AI). It is not surprising that not all tasks involved in Systematic Literature Review (SLR) planning, execution, and reporting have been fully automated to date. Our research indicates a strong inclination to leverage AI, particularly Machine Learning (ML), to facilitate the paper screening process, which entails sifting through thousands of candidate papers to identify relevant ones. Natural Language Processing (NLP) and ontologies prove especially beneficial in handling semantic data for various tasks, although there is a paucity of studies in these domains.

The findings highlight the need for a strategic roadmap for AI-led research, development, and implementation across different dimensions. Our primary objective is to foster the growth of a vibrant AI-based Literature Reviews (AILR) culture in the Information Systems (IS) field, offering enriching experiences for researchers at all stages of the research process—from authors to reviewers to industry professionals. The potential for extending AI-based tools and approaches beyond the IS field, particularly for design science researchers, holds great promise. We envision a future where IS researchers actively engage in discussions and reflections on how to optimally harness AI to advance their work.

B. Future Work

The future work outlined in the provided passage encompasses a comprehensive and forward-thinking strategy for advancing the field of AI-based literature reviews. Initially, the focus is directed towards extending the application of AI across various phases of the systematic literature review (SLR) process. While the current emphasis is on paper screening, the call is for a more encompassing integration, suggesting a desire to leverage AI capabilities throughout the entire SLR workflow. This expansion could lead to more nuanced and sophisticated automation, enhancing the efficiency and effectiveness of literature review processes.

Additionally, the passage underscores the importance of exploring advanced technologies, such as Natural Language Processing (NLP) and ontologies, for semantic data analysis in the context of literature reviews [16]. This suggests an aspiration to move beyond basic automation and delve into the realms of semantic understanding, potentially enabling AI systems to discern and interpret the underlying meaning of academic content. Moreover, the envisioned future involves broadening the application of AI-based tools and methodologies to domains beyond Information Systems (IS), emphasizing the need for transferability and interdisciplinary collaboration. This push for broader applicability aligns with the broader trend of fostering cross-disciplinary knowledge exchange and collaboration.

Furthermore, the future work envisions a significant enhancement of the user experience for researchers engaging with AI tools in the SLR process. This user-centric approach aims to make AI more accessible to individuals with varying skill levels, fostering inclusivity and democratizing the use of advanced technologies in academia. Simultaneously, there is a recognition of the importance of establishing benchmarks and evaluation criteria to assess the effectiveness and efficiency of AI-driven SLR processes. This emphasis on standardization reflects a commitment to ensuring robust and comparable outcomes in the application of AI methodologies to literature reviews. Finally, ethical considerations emerge as a crucial aspect of the envisioned future work, with a call to address ethical implications and develop guidelines for responsible AI implementation in research processes. This reflects a conscientious approach towards deploying AI in a manner that upholds ethical standards and promotes responsible conduct in academic research. In summary, the future work outlined in the passage is characterized by a holistic vision, encompassing technological advancements, usability improvements, interdisciplinary applications, ethical considerations, and a commitment to standardization in the realm of AI-based literature reviews.

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