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EDITORIAL

Systematic Review Writing by Artificial Intelligence: Can Artificial Intelligence Replace Humans?

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Publications are aplenty, particularly during the COVID-19 pandemic. As of February 10, 2022, there are 241,998 publications on the Web of Science Core Collection. Of these publications, 22,457 are review articles, and 147,381 are articles. The United States of America (n = 67026) and the Republic of China (n = 23,929) contributed to most of the pandemic publications. This list of research is enormous and continues to explode. Efforts to synthesize published evidence are becoming increasingly impractical because of the deluge of published evidence. Non-synthesized information in human language text is challenging to use in clinical practice.

Systematic reviews locate, assess, and synthesize relevant research findings on a health topic, making the information easily accessible to decision-makers [1]. A systematic review summarizes the literature on an existing clinical topic based on eligibility criteria. A review takes over 1000 hours of highly skilled manual labor to complete [2]. From the formulation of a query through publication, it took an average of 28 months for authors to complete a review (n = 14, range 18-46 months) [3]. From protocol registration to publication, systematic reviews registered with PROSPERO took an average of 67 weeks [4].

The time required to complete a review is highly variable. The time required will vary based on the review's topic, the authors' experience, the methods used (e.g., the number of attempts to collect unpublished data), the number of papers included, and the editorial team's help. However, authors may predict the time required by considering the tasks involved and the time needed to finish each task. These tasks include literature search, study selection, critical appraisal of the literature, data extraction, data analysis, text analysis, content writing, journal selection, reference and document management [5]. Even though they are very thorough, systematic review methods cannot keep up with the massive published information. Manual processes used to write systematic reviews are unsustainable. Once published, reviews quickly become obsolete.

Artificial Intelligence is the "science and engineering of making intelligent machines, especially intelligent computer programs" [6]. It is the ability of a machine to do cognitive functions (i.e., reasoning, perceiving, decision-making, problem-solving) [7]. AI aims to imitate human-like behavior [8]. For example, the average reading time of radiologists is approximately 6.5 minutes per CT scan, while their AI requires only 2.73 seconds [9]. Because humans speak around 150 words per minute but can write only 40 words per minute on average, an efficient voice recognition function will be useful for devices like computers to transform speeches into machine-readable texts [10]. Covidence reduces the time to write systematic reviews by up to 30% [11].

Researchers have developed methods to semi-automate systematic review writing through use of artificial intelligence. Machine learning (ML) and natural language processing (NLP) are commonly used to semi-automate systematic review writing [12]. ML employs computer algorithms that improve over time because of

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repeated data input. ML is similar to logistic regression, which is frequently employed in epidemiology. It analyzes enormous volumes of data using statistical modeling [13]. Without being programmed, the model makes predictions or decisions. For example, the ML model calculates the likelihood that an article is relevant and included in the systematic review. On the other hand, NLP analyzes vast amounts of text. The computer understands the articles' contents by analyzing the human language texts. It extracts information and insights from the articles and organizes them [14]. In contrast to solely syntactic text processing, NLP can isolate and analyze the underlying semantic meaning. Text categorization and data extraction are the two most common NLP technologies used in systematic reviews [15,16]. Text classification arranges documents

Table 1: The systematic review toolbox.

Systematic Review Processes and their Tools	Link	Description
Research Rabbit for literature search [18]	https://www.researchrabbit.ai/	Research Rabbit is a tool for mapping the literature. It searches prior and subsequent researches concerning submitted articles. It uses visualization, demonstrating relationships between relevant papers. The author can use the platform to share the content with the rest of the team.
Covidence for study selection [11]	https://www.covidence.org/	Covidence is a web-based software platform managing systematic review writing. Besides study selection, it includes full-text review, bias appraisal, data extraction, and data export into RevMan.
RobotReviewer for critical appraisal of the literature [19]	https://www.robotreviewer.net/	The RobotReviewer is an ML system that evaluates biases in randomized controlled trial studies.
Lateral for data extraction [20]	https://www.lateral.io/	Lateral searches for the common terms across all articles at once. It shows similar texts as search results. Lateral can automatically tabulate data from relevant articles.
GRADEpro for data Analysis [21]	https://www.gradepro.org/	GRADEpro is a RevMan extension that generates a summary of findings table. GRADEpro leads you through developing guidelines, from scoping to summarizing the evidence to generating recommendations and disseminating them while effortlessly adhering to the GRADE approach. All final recommendations can be accompanied by carefully produced and consumer-oriented presentations and interactive decision aids to share and facilitate collaborative decision-making.
Scite_ for text analysis [22]	https://scite.ai/	Scite_ shows how research articles have been cited, making it easier for researchers to find and understand them. Researchers can read the context of a reference and determine whether it contains evidence that supports or refutes the citation statement. By compiling the citation statements in one location, a researcher can determine how other researchers interpreted and evaluated the article. Expert analysis and opinions on any topic can also be found by searching citation statements and claims.
Scalenut for content writing [23]	https://www.scalenut.com/	Scalenut writes content based on the keywords provided by the researcher. The contents are based on the most commonly searched websites reporting the research topic. Sentences are written within seconds. In the end, the researcher determines the relevance of the generated content.
Journal/Author Name Estimator (JANE) for journal selection [24]	https://jane.biosemantics.org/	JANE searches for journals, articles, or authors using the submitted abstract or title. Likewise, it identifies articles to cite. JANE searches PubMed documents to match journals, authors, or articles with your manuscript.
Zotero for managing references [25]	https://www.zotero.org/	Zotero creates references and bibliographies. It collects, organizes, cites, and shares research sources among research team members.
Prisma Flow Diagram for managing the document [26]	https://estech.shinyapps.io/prisma_flowdiagram/	Prisma Flow Diagram is an R package and a Shiny application that generates interactive flow diagrams under the PRISMA 2020 reporting guidelines. The R version has tooltips and hyperlinks to facilitate interaction. The shiny version does not require coding or R skills.

based on predefined criteria [17]. For example, it uses titles and abstracts to identify randomized controlled trial studies. Data extraction identifies specific words or numbers or combinations that match a variable of interest. For instance, NLP will extract numerical values from heart rate measurements to determine the influence of facemasks on heart rate during exercise.

The Systematic Review Toolbox is a web-based catalog of tools that support various tasks in systematic review writing. The comprehensive toolbox list is at http://systematicreviewtools.com/index.php [4]. Below are sample tools used in semi-automating systematic review writing (Table 1) [18-26].

AI has the potential of outperforming humans in systematic review writing. However, full automation without human intervention is from reality. Even if the rate at which machines think could be virtually infinite or infinitely fast compared with humans, machines cannot fully automate systematic review writing. AI cannot comprehend the most basic of the real world. However, AI can help facilitate systematic review writing through semi-automation. It can make processes in systematic review writing efficient; however, AI cannot replace humans in ensuring the validity of results, application of results to real-life scenarios, and problem-solving. Humans remain involved in systematic review writing rather than being replaced. The human judgment remains necessary, especially for research generating questions, problem analysis, and solving [27].

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