Evidence Based Library and Information Practice

Commentary

Systematic Searching in a Post-Pandemic World: New Directions for Methods, Technology, and People

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Introduction

In January 2019 we concluded our book, *Systematic Searching: Practical Ideas for Improving Results*, by asking the question, Where do we go from here?" We would like to begin to answer this question by assessing how the search landscape has changed since our book was published (Levay & Craven, 2019). The COVID-19 pandemic has accelerated change and led us in new directions, as well as confirmed some of the issues that we already anticipated.

This commentary focuses on the challenges facing information specialists and others who are engaged in searching to support systematic reviews and other evidence syntheses in healthcare, briefly reviewing the main developments that have occurred in relation to methods, technology, and people. Throughout this commentary, we refer to information specialists as a general term to describe any information

professional involved in systematic searching. This article is intended to prompt discussion about how the information profession might need to adapt, and it is not a comprehensive summary of the recent literature. In addition, we have not covered information about how to conduct systematic searching, as a new guide to that topic is available (Foster & Jewell, 2022).

Methods

We have to ensure that we keep our methods up to date to meet new challenges so that we continue delivering the right evidence at the right time.

Living Reviews and Living Guidelines

The importance of keeping systematic reviews and guidelines up to date became vitally important during a global pandemic caused by a new disease. Living reviews, which are continually updated to incorporate relevant new evidence as it becomes available, had been established several years before the pandemic (Elliott et al., 2017). COVID-19 meant we had to accelerate the process of developing living guidelines to incorporate the findings of living reviews into evidence-based recommendations. A living guideline contains one or more recommendations that are "kept current by an optimized guideline-updating process that accounts for potentially consequential evidence as soon as or shortly after it becomes available" (El Mikati et al., 2022, p. 1155).

A key question when developing living guidelines is whether to search broadly to cover a whole topic or to run several, targeted searches (McDonald et al., 2023). The decision is affected by how often the evidence is likely to change, the number of databases or other search techniques required, the frequency of the searching, the current level of uncertainty in the evidence, and the time available for processing the search results. Reporting the searches for a living guideline is challenging as the recommendations could be based on different strategies, date limits, and sources (Metzendorf et al., 2022).

COVID-19 has shown that it is feasible to establish living reviews that support living guidelines. The challenge now is to extend the living approach in topics other than COVID-19. This will require thinking about the issues we explore in the following sections relating to types of evidence, using technology efficiently, and developing new skills.

Searching for the Right Types of Evidence

As information specialists, we had to identify the appropriate types of evidence for the COVID-19 pandemic. There is an ongoing debate about how systematic reviews can incorporate mechanistic evidence, which is derived from studies that explain the factors, interactions, and other mechanisms that are responsible for a phenomenon (Greenhalgh et al., 2022). For example, reviews on the effectiveness of face masks for stopping the spread of COVID-19 might consider a wide range of study designs from various disciplines, including in vitro experiments, imaging data, aerosol science, and engineering research (Greenhalgh et al., 2022). Search strategies focusing on data from clinical trials would miss significant areas of this evidence. These are new subject areas for many information specialists in healthcare settings, requiring us to explore the appropriate sources and search techniques to retrieve mechanistic evidence.

The international focus on mechanistic evidence highlighted a long-standing issue on how we identify and synthesize evidence to understand how complex interventions operate (Greenhalgh & Peacock,

2005). It was even more important than ever that we discussed with review teams the types of evidence required instead of relying on our familiar processes. We need to apply this approach in all systematic reviews rather than relying on standardized methods. We must choose the appropriate search approaches (Cooper et al., 2022) and sources (Levay et al., 2022a) for the topic and the type of evidence required. We know that using different search approaches and a wide range of sources takes longer and requires more resources (Briscoe et al., 2022). We have to resolve these logistical challenges with review teams or else we risk missing relevant evidence.

Incorporating Preprints

Accessing the latest evidence was crucial when millions of lives were potentially at risk from COVID-19. Preprints, which are full manuscripts of papers made available before or in parallel with the peer review process (Clyne et al., 2021), were required when our core sources could not provide the up-to-date studies needed to understand COVID-19.

We have to devise methods to deal with the challenges that we face when incorporating preprints into evidence synthesis (Khalil et al., 2021). It is important to update processes so that we can identify whether the preprints included in a systematic review changed or were retracted after they had been peer reviewed (Brierley et al., 2022). Our reference management practices need updating, as a preprint and the linked final article are not strictly duplicates, although they must not be double counted in a meta-analysis. Preprint servers are also of varying scope and quality (Kirkham et al., 2020), often lacking the sophisticated interfaces needed to write precise search strategies. Some of these technical issues have been resolved since preprints became available on Europe PubMed Central (Rosonovski et al., 2023).

Technology

We must deploy technology effectively to be able to handle increasing complexity, higher volumes, and different types of evidence.

Study-Based Registers

Study-based registers (databases in which all references to a study are available in a single record) have been available for several years to make evidence easier to find (Shokraneh & Adams, 2019). For example, a study-based register covering clinical trials might bring together references to the protocol, main results, and sub-group analyses into a single record. COVID-19 gave fresh impetus to these registers, as they facilitated rapid searches, while reducing research waste and duplication between teams.

A number of open access COVID-19 study-based registers have been established, such as the Cochrane COVID-19 Study Register (Metzendorf & Featherstone, 2021) and Epistemonikos COVID-19 L·OVE (Verdugo-Paiva et al., 2022). They have been reviewed favourably in terms of completeness and timeliness (Butcher et al., 2022; Pierre et al., 2021).

We would benefit from having guidance to help us identify when to use registers in place of separate databases. Barriers to uptake include technical ones (such as how easy it is to export the results) or personal ones relating to confidence with using unfamiliar databases and other search tools, such as study-based registers. Registers are time consuming and expensive to maintain so extending this approach would require the major producers of systematic reviews to invest in the infrastructure.

Machine Learning Classifiers

A feature in facilitating up to date and comprehensive study-based registers and living systematic reviews was the widespread adoption of machine-learning classifiers. Machine learning deploys algorithms that learn to perform a specific task in order to make predictions based on the training data that has been provided (Thomas et al., 2021). In the context of systematic reviews, the training data is often the decisions on which papers to include or exclude. The data enables the algorithm to "learn" which words and phrases are more likely to lead to a paper being included, in comparison to those indicating that the paper should be excluded (O'Mara-Eves et al., 2015).

Machine learning requires large quantities of training data, and this takes time to acquire, validate, and process (Stansfield et al., 2022). It would be fruitful to share machine-learning algorithms across topics or domains so that each review team does not have to start afresh. Machine learning has been used to identify randomized controlled trials (Thomas et al., 2021) and to populate the Cochrane COVID-19 Study Register (Shemilt et al., 2022). As machine learning becomes more fully incorporated into workflows for screening search results (Chappell et al., 2023), we may be able to provide broader, less precise, strategies for some reviews. Information specialists can advise review teams, and we should be involved in decisions about how and when to use machine learning.

Developing Search Strategies

Technological developments are driving change even in areas where we have well-developed practice. Numerous tools are available to help us design and deliver searches, as listed on the Systematic Review Toolbox website (Johnson et al., 2022). More changes are coming that will affect how we do this work.

Automated indexing will affect the sensitivity and precision of our strategies, encouraging us to review how we develop and test searches. To aid selection of controlled vocabulary terms, the National Library of Medicine (NLM) has had a fully automated process for indexing MEDLINE records with Medical Subject Headings (MeSH) since April 2022 using the Medical Text Indexer (MTI) (National Library of Medicine, 2022). There are initial indications that MTI, compared to human indexers, will be responsible for applying more MeSH terms to each record, omitting age-related check tags, and choosing headings from different levels in the hierarchy (Chen et al., 2023). This increasing automation might influence the effectiveness of particular search strategies. As a result, we might need to review any search strategies, including validated search filters, written before fully automated indexing was implemented.

Another area worth exploring is the potential of using search visualization to replace the familiar form-based method of inputting queries into services such as PubMed. For example, there has been some success in testing a visual interface for creating and editing searches, such as the one provided by 2Dsearch (Svarre & Russell-Rose, 2022). We will benefit from collaborating with computer scientists and software engineers to develop the tools we need. These conversations can be facilitated by using design principles relevant to systematic searching (MacFarlane et al., 2022).

Can we use artificial intelligence (AI) to generate search strategies? Text-generation systems are already being rolled out to question-answering services in familiar search engines, such as Bing and Google. We are now seeing attempts to apply generative AI to evidence synthesis with mixed results (Qureshi et al., 2023). ChatGPT-3.5, launched in November 2022, can generate seemingly plausible PubMed strategies, if prompted with the right question (Wang et al., 2023). These strategies would not currently pass through

our peer-review checklists, as they can contain serious errors, such as subject headings that do not actually exist in MeSH (Wang et al., 2023).

We should not, however, over-emphasize the fact that strategies generated by ChatGPT-3.5 are currently "unusable" (Qureshi et al., 2023, p. 2). The use of third-party plug-ins will improve the accuracy of ChatGPT-4.0, which is currently available to subscribers. Generative AI will probably be incorporated into bibliographic databases, with trials imminent in Scopus and Web of Science, among others (van Noorden, 2023). The technology is going to improve massively and very quickly!

As large language models are fundamentally based on prediction, the quality of their training data is vitally important. We know, however, that many published systematic reviews are based on low-quality searches (de Kock et al., 2020). Any strategy generated from this poor data is likely to be flawed. Longer term, we should take steps to ensure that AI systems are learning from high-quality training data. The most effective AI systems for use in evidence synthesis will be those that incorporate the recommendations from the International Collaboration for the Automation of Systematic Reviews (ICASR) (Beller et al., 2018).

AI cannot be ignored and so information specialists must be ready to lead the transformation of working practices. It is probable that we will see human-in-the-loop systems develop, rather than purely automated evidence syntheses. We should grasp the opportunity to expand our roles into troubleshooting, user education, evaluation of sources, and validation of results.

People

Several chapters in our book explored the benefits of effective communication and collaboration, and these skills have never been as important as they were during the COVID-19 pandemic.

Collaboration

Effective collaboration might be between information specialists and the wider team, or it might feature groups of information professionals in local, national, and international networks (Waffenschmidt & Hausner, 2019). Collaboration between information specialists was particularly valuable during COVID-19, which Caroline De Brún (2022) has helpfully summarized as involving:

- Supporting other librarians
- Reducing duplication of effort
- Sharing best practices
- Problem solving and local support

These principles were demonstrated by the Librarian Reserve Corps (LRC), a voluntary network of medical, health sciences, and public health librarians, who came together to provide an evidence-based response to the international emergency (Callaway, 2021). The LRC has published a valuable guide that draws on the lessons of COVID-19 to guide searching during future emergencies (Brody et al., 2023). As another example, the European Association for Health Information and Libraries (EAHIL) Evidence Based Information Special Interest Group (EBI-SIG) is working on a project to create a living open access library of search strategy resources (EBI-SIG, 2023). We have also seen the launch of the *searchRxiv* website for sharing, archiving and identifying search strategies (CABI Digital Library, 2023), which demonstrates the value of large-scale collaborative efforts.

Networking and developing relationships are vital for keeping up to date with other information specialists and organizations.

Communication

Communication is a key skill for facilitating collaboration. Many of us have been using Zoom, Microsoft Teams, and other platforms far more than we had ever envisaged five years ago. This certainly helped to develop international links. We ought not overlook how these networks helped to overcome isolation and promote wellbeing in a time of lockdowns and other pandemic restrictions (De Brún, 2022).

Communication skills are as important as technical knowledge in training to become an information specialist (Levay et al., 2022b). We must be able to demonstrate that our searches are reliable, transparent, and reusable (Sampson, 2019). The Preferred Reporting Items for Systematic reviews and Meta-Analyses literature search extension (PRISMA-S) is a guide to reporting search histories in a replicable and transparent way (Rethlefsen et al., 2021). The checklist is also a useful communication tool, as it encourages us to share our work clearly and completely. We would encourage all information specialists to integrate PRISMA-S into their processes.

Skills and Training

Skills and training were a central theme in our book to ensure information specialists could lead change and drive improvements. The evidence on the value of expert searchers has continued to accumulate since then (Ramirez et al., 2022).

Information specialists need to develop the skills to promote equality, diversity, and inclusion through our work in systematic reviewing. For example, with appropriate experience, writing a search protocol is an opportunity to help tackle health inequalities, if we select appropriate data sources, ensure the search strategies cover diverse populations, and deal with underrepresentation in the literature (Naicker, 2022). Important work has been done to show how we might discuss outdated, discriminatory, and other potentially inappropriate terminology with review teams, and then consider how we should report these search terms carefully when they are required in a strategy (Townsend et al., 2022).

There are opportunities to learn from the experiences of data librarians, who are involved with managing the research lifecycle, data curation, data analysis, and visualization (Ashiq & Warraich, 2022). Data management skills would be useful for managing data generated during a systematic review, incorporating real-world evidence, advocating for open data, and gaining a better understanding of technical challenges.

In addition, all information specialists would benefit from acquiring data literacy and computational-thinking skills to help us to solve problems with technology. Having this awareness opens up new opportunities to introduce technology into our work, through learning how to code, understanding programming languages, developing apps, or using packages from Github. Bibliometrix (Aria & Cuccurullo, 2017) and similar packages perform well-established tasks quickly and effectively with powerful results, such as identifying phrases in a set of text, checking citation networks, and topic modelling. Evaluating these tools and knowing how and when to use them appropriately will be essential for everyone, including those who do not learn to code themselves.

The purpose of developing these skills is to improve systematic reviews through the value information specialists add to teams. It is not just about doing the searches, it is about educating review teams on automation, showing them how to deploy technology and improving their processes. We have the skills and experience to be agents of cultural change as we help teams to integrate AI and other technology into existing processes. We will do this effectively where we can show that the new ways of working uphold the values of accuracy, transparency, and accountability (Arno et al., 2021).

Conclusion

The COVID-19 pandemic has clearly had a significant impact on the methods and technology we use for systematic searching, accelerating some trends and introducing new challenges. In terms of methods, searching for evidence on COVID-19 has focussed on living reviews and guidelines, the use of mechanistic evidence, and new sources, such as preprints. The increasing volume and complexity of evidence necessitates better use of technology, such as study-based registers, machine-learning classifiers, and visualization software. International collaboration was valuable during the pandemic, and it was facilitated through good communication. We can promote equality, diversity, and inclusion through our searches. New skills, such as data management and coding, will become increasingly valuable. Automation will not result in our spending less time on systematic searching, but it may change how we focus our efforts.

Fundamentally, we stand by the conclusion we drew in our book, *Systematic Searching: Practical Ideas for Improving Results,* that these methods and technologies will only be deployed effectively if information specialists are involved and set the agenda. The five years since 2019 have shown that systematic searchers need to be flexible, creative, and at the forefront of innovation: we expect these trends will intensify in the coming years.

Author Contributions

Paul Levay: Conceptualization (equal), Writing – original draft (lead), Writing – review and editing (equal) **Jenny Craven:** Conceptualization (equal), Writing – original draft (supporting),Writing – review and editing (equal)

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