

AI in evidence synthesis and guidelines: Should we trust the machines?

Zachary Munn

October 2027

2026 INC International Nursing Conference
Nursing Intelligence in the AI Era:
Strategic Empowerment of Research, Education, and Practice

October 19th - 20th, 2026
Swiss Grand Hotel, Seoul, Korea



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We acknowledge and pay our respects to the Kaurna people, the traditional custodians whose ancestral lands we gather on.

We acknowledge the deep feelings of attachment and relationship of the Kaurna people to country and we respect and value their past, present and ongoing connection to the land and cultural beliefs.



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Interests/Disclosures/Overview



Director HESRI, School of Public Health



GRADE Centre Director and Working Group Member



Past-Chair Guidelines International Network (GIN)



Funding for Systematic Reviews and Guidelines



Head of Evidence Synthesis Taxonomy Initiative



Involved in many Methodology Groups/Networks

NHMRC Investigator Grant Funding APP1195676

Website: <https://health.adelaide.edu.au/hesri/>



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The development of software to support multiple systematic review types: the Joanna Briggs Institute System for the Unified Management, Assessment and Review of Information (JBI SUMARI)

Zachary Munn,¹ Edoardo Aromataris,¹ Catalin Tufanaru,¹ Cindy Stern,¹ Kylie Porritt,¹ James Farrow,² Craig Lockwood,¹ Matthew Stephenson,¹ Sandeep Moola,¹ Lucylynn Lizarondo,¹ Alexandra McArthur,¹ Micah Peters,¹ Alan Pearson¹ and Zoe Jordan¹

¹The Joanna Briggs Institute, The University of Adelaide, Adelaide, South Australia, ²Farrow Norris, Sydney, Australia

ABSTRACT

Aim: Systematic reviews play an important role in ensuring trustworthy recommendations in healthcare. However, systematic reviews can be laborious to undertake and as such software has been developed to assist in the conduct and reporting of systematic reviews. The Joanna Briggs Institute and its collaborating centres consist of thousands of researchers, academics and clinicians across the globe conducting systematic reviews of various types. To support them in their work, modern software and online tools are required. Our aim was to develop a software program to support systematic reviewers across the globe.

Methods: A working party was formed with extensive consultation with members of the Joanna Briggs Collaboration focusing on ideal features of a software program to support systematic reviews. The new systematic review software was built using an agile methodology and designed to be a modern web application.

Results: The new systematic review software, the Joanna Briggs Institute System for the Unified Management, Assessment and Review of Information (JBI SUMARI), was successfully developed through an iterative process of development, feedback, testing and review. The software is now available (<https://www.jbisumari.org/>) and supports the entire systematic review process for different types of systematic reviews.

Conclusions: An agile software development approach combined with wide consultation and user testing can facilitate systematic review software design and development. This new software can support systematic reviews and guideline developers to create systematic reviews for a diverse range of questions.

Key words: Joanna Briggs Institute, meta-analysis, software, systematic review

Int J Evid Based Healthc 2019; 17:36–43.

Disclaimer:

Product developer (once upon a time)

Not an AI or ML expert



Interests/Disclosures/Overview

....I use AI all the time*

Our team use AI to assist in guideline development (with checks and oversight)

- Creation of health outcome descriptors
- SWAR of AI supported searching, screening and selection
- Support integrity checking
- Double check RoB assessments
- Plain language conversions
- Wording of survey preambles
- Check R code

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*note: no AI was used in the development of this presentation (except where credited) – I am accountable for all mistakes/errors and terrible formatting in this presentation



Challenges in Synthesis and Guidelines

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The Evidence Synthesis Family



Systematic reviews

Mixed methods reviews

Qualitative evidence synthesis

Rapid reviews

Realist synthesis

Umbrella/Overviews Reviews

Evidence (gap) maps

Scoping reviews

....and more!



Clarifying differences between review designs and methods

David Gough III, James Thomas and Sandy Oliver

Systematic Reviews 2012 1:28

<https://doi.org/10.1186/2046-4053-1-28> | © Gough et al.; licensee BioMed Central Ltd. 2012

Received: 4 January 2012 | Accepted: 19 March 2012 | Published: 9 June 2012

[Open Peer Review reports](#)

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Types of Systematic Reviews

1. Interventions/Effectiveness
2. Qualitative/Experiences
3. Costs/Economic Evaluations
4. Prevalence or Incidence
5. Diagnostic Test Accuracy
6. Etiology and Risk
7. Policy/Opinion
8. Measurement properties
9. Prognostic
10. Methodological
11. Preferences and values
12. Animal/bench studies

...and more!

Munn et al. *BMC Medical Research Methodology* (2018) 18:5
DOI 10.1186/s12874-017-0488-4

BMC Medical Research
Methodology

CORRESPONDENCE

Open Access



What kind of systematic review should I conduct? A proposed typology and guidance for systematic reviewers in the medical and health sciences

Zachary Munn¹, Cindy Stern, Edoardo Aromataris, Craig Lockwood and Zoe Jordan

Abstract

Background: Systematic reviews have been considered as the pillar on which evidence-based healthcare rests. Systematic review methodology has evolved and been modified over the years to accommodate the range of questions that may arise in the health and medical sciences. This paper explores a concept still rarely considered by novice authors and in the literature: determining the type of systematic review to undertake based on a research question or priority.

Results: Within the framework of the evidence-based healthcare paradigm, defining the question and type of systematic review to conduct is a pivotal first step that will guide the rest of the process and has the potential to impact on other aspects of the evidence-based healthcare cycle (evidence generation, transfer and implementation). It is something that novice reviewers (and others not familiar with the range of review types available) need to take account of but frequently overlook. Our aim is to provide a typology of review types and describe key elements that need to be addressed during question development for each type.

Conclusions: In this paper a typology is proposed of various systematic review methodologies. The review types are defined and situated with regard to establishing corresponding questions and inclusion criteria. The ultimate objective is to provide clarified guidance for both novice and experienced reviewers and a unified typology with respect to review types.

Keywords: Systematic reviews, Evidence-based healthcare, Question development



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Task	Description	Classification
1. formulate review question	Decide on the research question of the review.	preparation
2. find previous SR	Search for SR that answers the same question.	
3. write the protocol	Provide an objective, reproducible, sound methodology for peer review.	
4. devise search strategy	Decide on databases and keywords to find all relevant trials.	
5. search	Aim to find all relevant citations even if many irrelevant ones included.	retrieval
6. de-duplicate	Remove identical citations.	
7. screen abstracts	Based on titles and abstracts, remove definitely-irrelevant trials.	appraisal
8. obtain full text	Download, request copies from authors, inter-library loans, etc.	
9. screen full text	Exclude irrelevant trials.	
10. snowball	Follow citations from included trials to find additional trials.	synthesis
11. extract data	Extract outcome numbers and associate with trial arm.	
12. synthesize data	Convert extracted data to common representation (usually average and SD).	
13. re-check literature	Repeat the search to find new literature published since the initial search.	write-up
14. meta analyze	Statistically combine the results from all included trials.	
15. write up review	Produce and publish the final report.	write-up

Systematic review automation technologies

Guy Tsafnat¹, Paul Glasziou², Miew Keen Choong³, Adam Dunn⁴, Filippo Galgani⁵ & Enrico Coiera⁶

Systematic Reviews 3, Article number: 74 (2014) | [Cite this article](#)



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Issues and Challenges in Evidence Synthesis

1. Approximately 80 reviews a day
2. Duplication/Redundant reviews
3. Poor quality/poorly reported
4. No impact in practice
5. Costly and time consuming
6. Out of date by the time they are completed
7. Incorrect approach/methods for the question

(Hoffman 2021, Møller 2018, Ioannidis 2016, Page 2016, Munn 2018)



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Ensuring high quality and efficient development of trustworthy guidelines

Planning and production - GIN McMaster checklist

Handbooks and guidance – NHMRC, GRADE

Reporting standards – RIGHT



Evaluate trustworthiness of a guideline – AGREE



Software – GRADEPro, MAGICApp, Covidence



Networking, registering guidelines, collaboration - GIN



Adapt and adopt – GRADE Adolopment

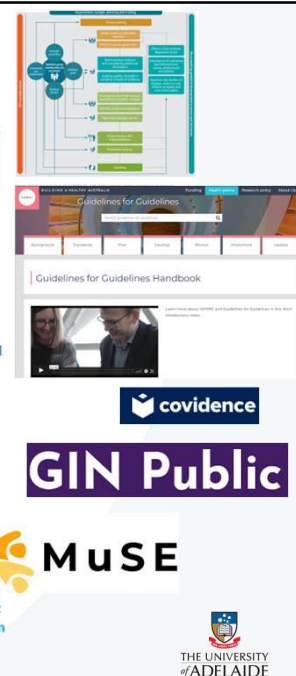
Engagement with community – MuSE/ GIN Public



For education and training – INGUIDE



International Guideline Development
Credentialing & Certification Program



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Guidelines - Costly and timely

Systematic reviews average 67.3 weeks

(Borah 2017)

Average guideline takes 18-30 months

(NHMRC)

Costs up to approximately 1 million AUD,

USD \$775000, 5 million CNY (NHMRC)

Countless person hours

Open Access Research BMJ Open Analysis of the time and workers needed to conduct systematic reviews of medical interventions using data from the PROSPERO registry

Rohit Borah,^{1,2} Andrew W Brown,^{2,3} Patrice L Capers,^{2,3} Kathryn A Kaiser^{2,3}

To cite: Borah R, Brown AW, Capers PL, et al. Analysis of the time and workers needed to conduct systematic reviews of medical interventions using data from the PROSPERO registry. *BMJ Open* 2017;7:e01245. doi:10.1136/bmjopen-2016-012455

► Publication history and additional material is available. To view please visit the journal (<http://dx.doi.org/10.1136/bmjopen-2016-012455>).

Received 5 May 2016
Revised 21 October 2016
Accepted 25 October 2016

ABSTRACT
Objectives: To summarise logistical aspects of recently completed systematic reviews that were registered in the International Prospective Register of Systematic Reviews (PROSPERO) registry to quantify the time and resources required to complete such projects.

Design: Meta-analysis.
Data sources and study selection: All of the 195 registered and completed reviews (status from the PROSPERO registry) with associated publications at the time of our search (1 July 2014).

Data extraction: All authors extracted data using registry entries and publication information related to the data sources used, the number of initially screened citations, the final number of included studies, the time between registration date to publication date and number of authors involved for completion of each publication. Information related to funding and geographical location was also reported when reported.

Results: The mean estimated time to complete the project and publish the review was 67.3 weeks.

Strengths and limitations of this study

- This study provides an updated estimate of the time and effort required to conduct and publish a systematic review using a large sample of recently published reviews across a variety of topics of medical interventions.
- The study is limited by incomplete reporting in both sources of the data—the review registry and the published articles.
- These data sources were cross-checked as data were available and conservative assumptions were stated and applied where necessary.

exponentially, as has the primary literature.¹ Since the body of primary literature has increased, conducting systematic reviews and meta-analyses has become a necessity to move accurately and comprehensively

Project planning

The process of developing a guideline can be long and complex — it needs good organisation and planning to be successful

Project planning

What to do
NHMRC requirements
NHMRC Standards
Useful resources
Professional

A guideline typically takes between 18-30 months to complete, with reported costs of up to approximately AUD \$1 million (NHMRC 2016). While much is underway as to how to accelerate the production of guidelines, the reality is that the fundamental processes of guideline development such as the evidence review, developing the recommendations and public consultation take time, careful planning and adequate resourcing.

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Guidelines - Inefficient

Much duplication in effort

Lack of automation

Hesitancy to adopt systematic review and guideline development tools

Lack of collaboration and sharing

Annals of Internal Medicine

Ideas and Opinions | 15 December 2020

Developing Guidelines Before, During, and After the COVID-19 Pandemic

Zachary Munn, PhD , Sara Twaddie, MSc, PhD , Duncan Service, MA (Hons), DipLis, Elaine Harrow, MA, Patrick Mbah Okwen, MD , Holger Schonemann, MD, PhD , and Per Olav Vandvik, MD, PhD

Author, Article, and Disclosure Information
<https://doi.org/10.7326/M20-4907>

“The process of developing trustworthy recommendations has often been plagued with inefficiencies, redundancies, duplication, and a lack of collaboration and sharing.”

“Members of the guideline and evidence-based health care communities have been working for years to improve this poorly functioning evidence ecosystem, yet the underlying collaborations, tools, and processes for wholesale efficiencies in the translation of evidence into practice were not widely established when the COVID-19 pandemic began.”

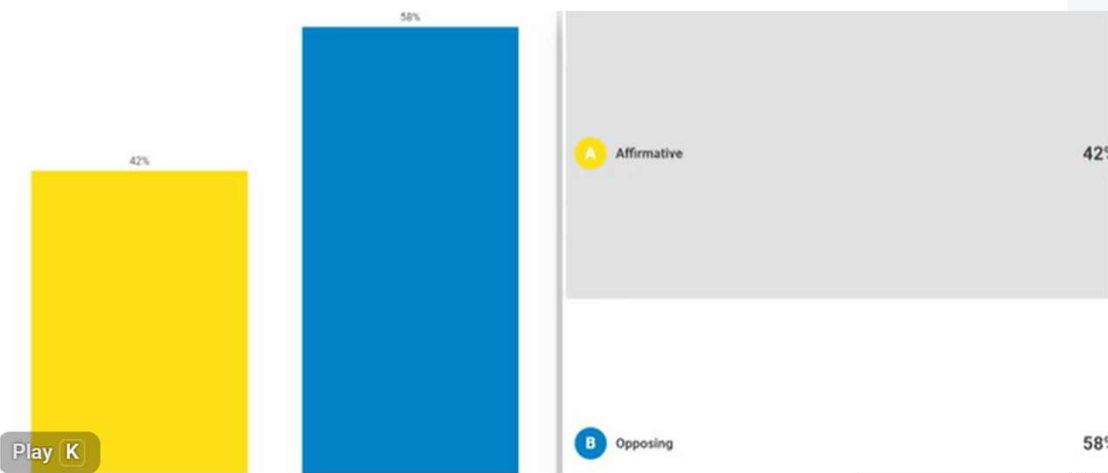


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Should AI replace humans in evidence synthesis?



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Agenda

1. AI and automation – a historical perspective
2. How AI works
3. Tools and uptake
4. What can't AI replace
5. Workflows and considerations



Timeline of Systematic Reviews

Timeline of Systematic Reviews



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Timeline of Systematic Reviews



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Timeline of Systematic Reviews



Treatise of the Scurvy



Pearson statistically combines studies on typhoid vaccine



Timeline of Systematic Reviews



Treatise of the Scurvy

Glass coins the term 'meta-analysis'



Pearson statistically combines studies on typhoid vaccine

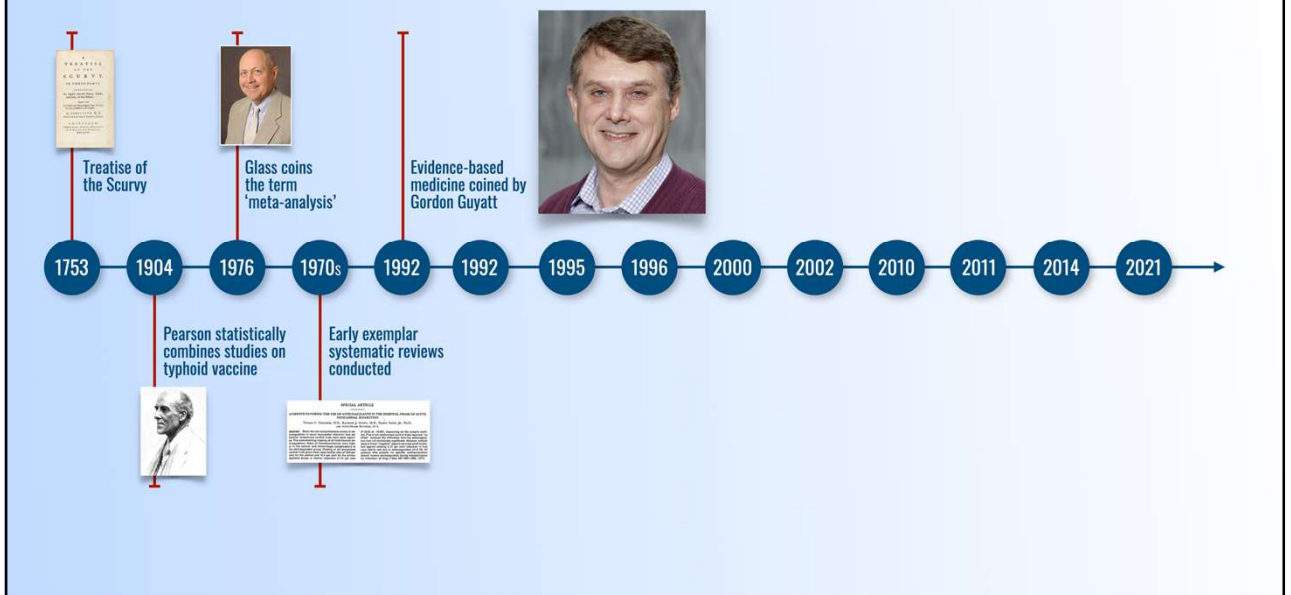


Timeline of Systematic Reviews



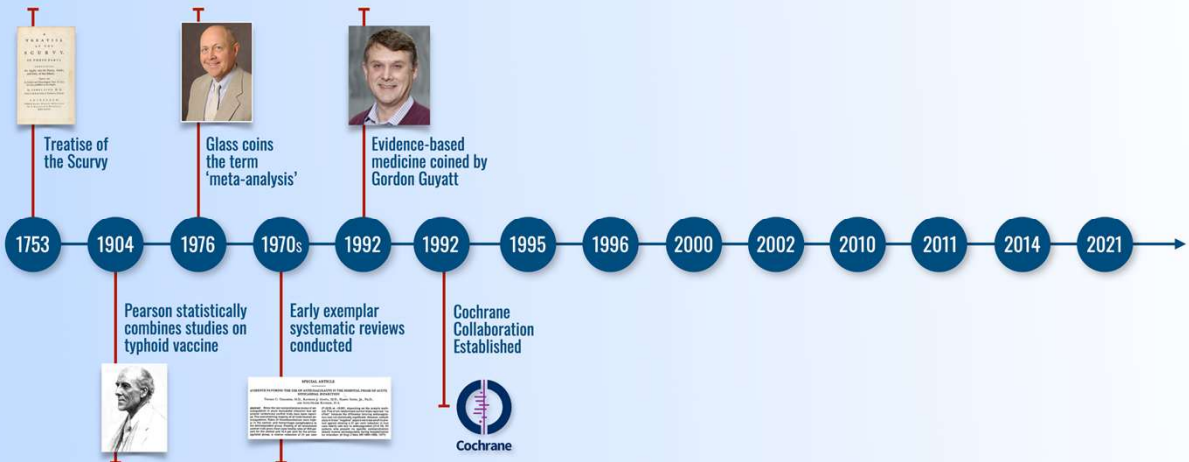
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Timeline of Systematic Reviews



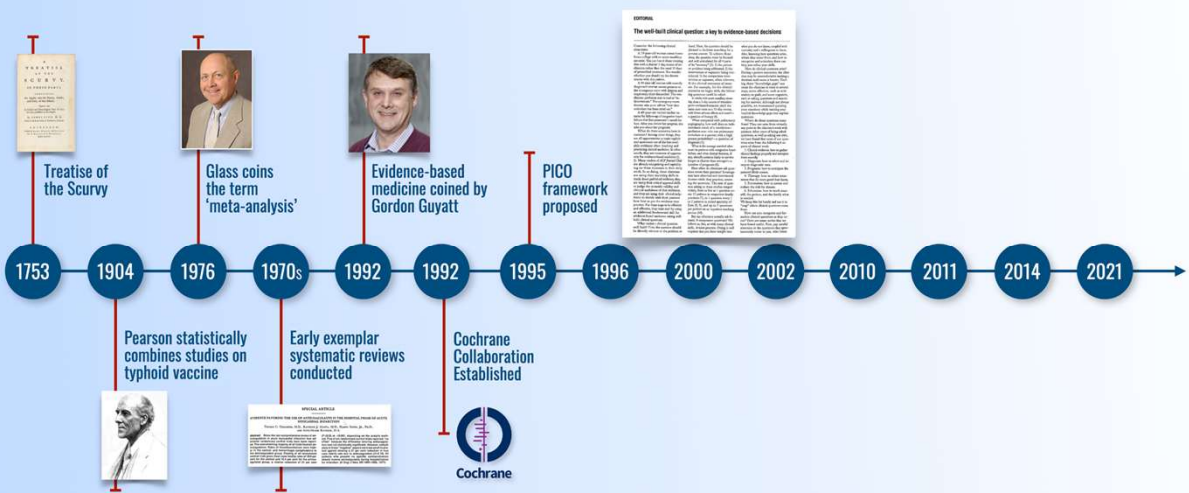
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Timeline of Systematic Reviews



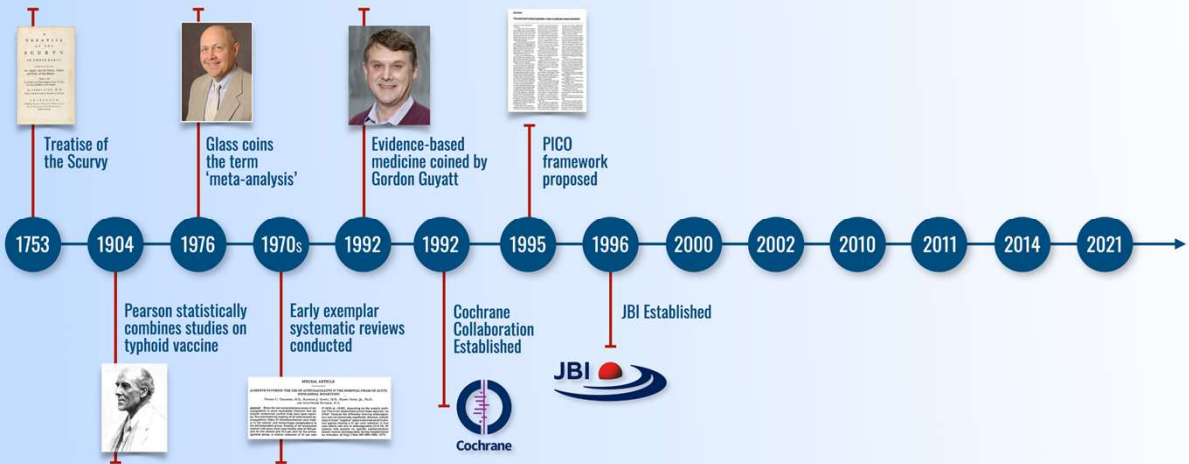
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Timeline of Systematic Reviews



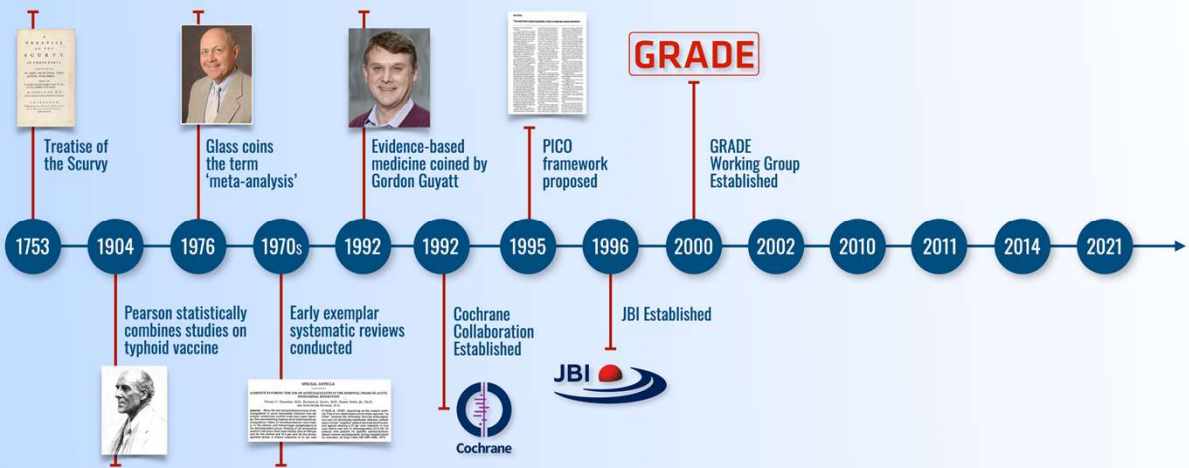
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Timeline of Systematic Reviews



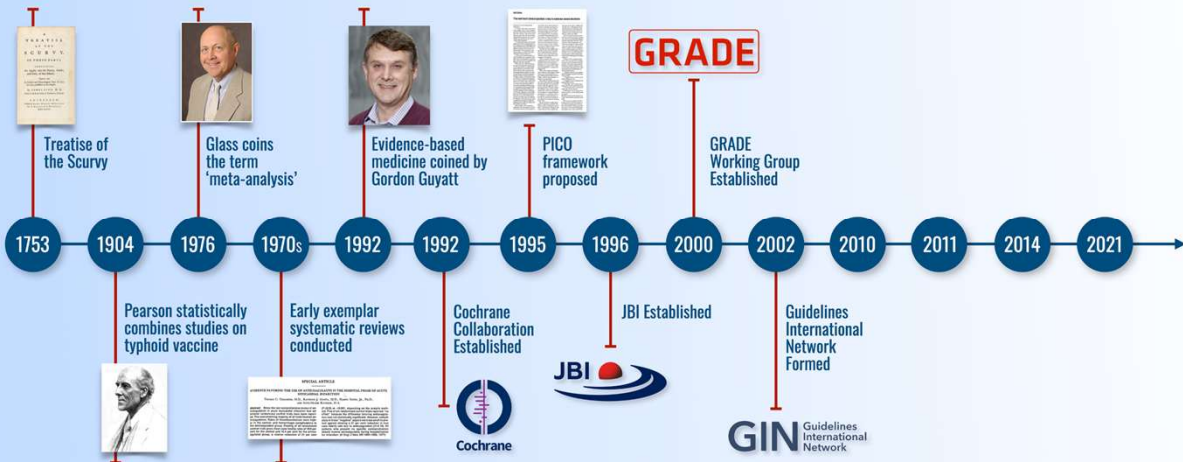
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Timeline of Systematic Reviews



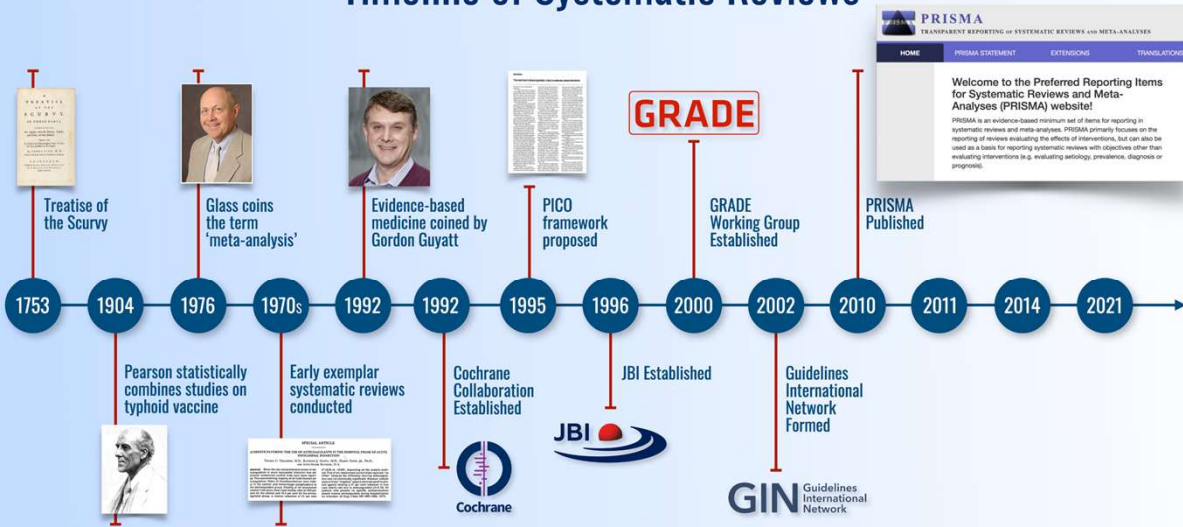
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Timeline of Systematic Reviews



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Timeline of Systematic Reviews



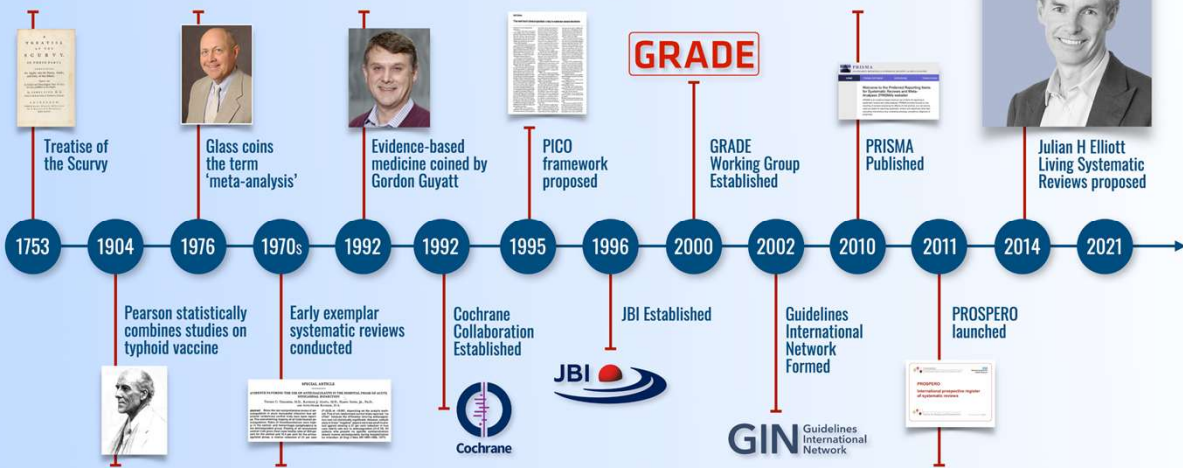
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Timeline of Systematic Reviews



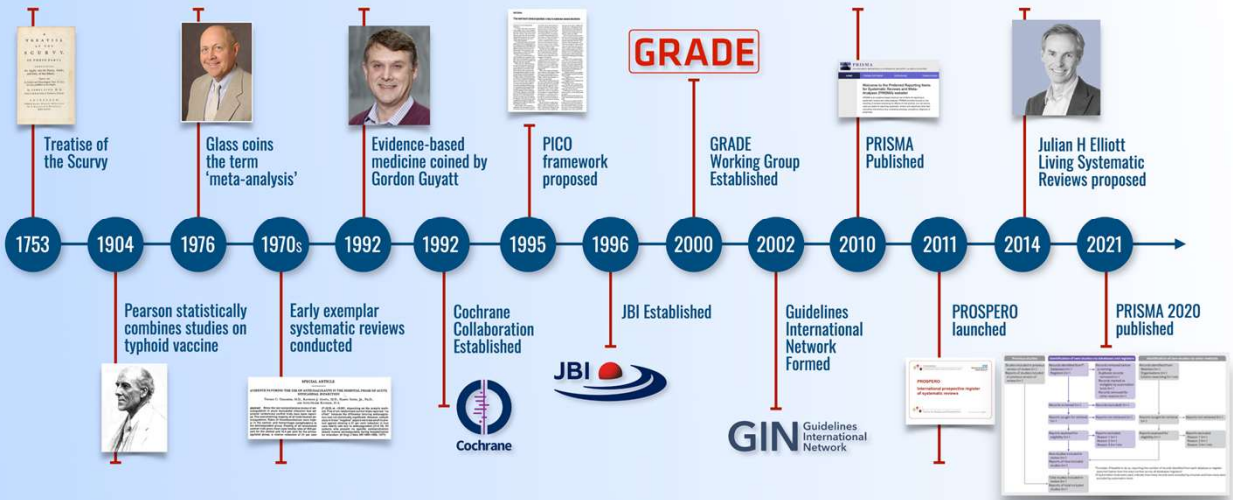
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Timeline of Systematic Reviews



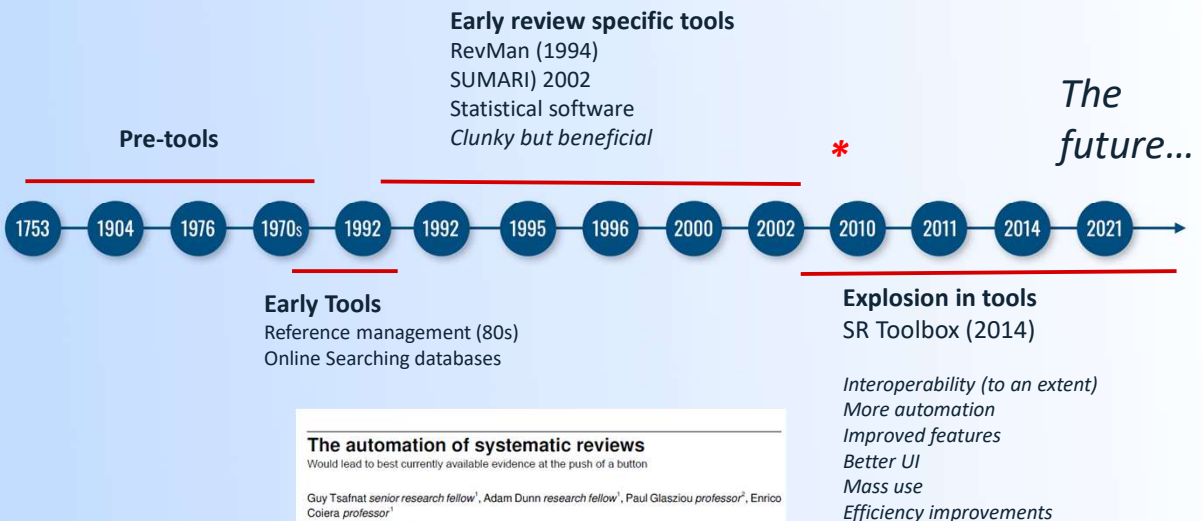
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Timeline of Systematic Reviews



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Timeline of Systematic Reviews



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Responsible AI in Evidence Synthesis (RAISE): guidance and recommendations

Contributors: James Thomas, Ella Fleming, Anna Noel-Storr

Date created: 2024-08-30 04:37 AM | Last Updated: 2024-10-04 03:36 AM

Category: Project

Wiki

Welcome to the home page of this project to develop guidance and recommendations for the responsible use of AI in evidence synthesis!

Papers for the project can be found here, along with links for your feedback.

Please follow this link to open the form to give feedback on the draft guidance. (We are following the ICMJE guidelines for determining authorship, so usually expect to be able to acknowledge...)

Read More

Files

Name

Modified

Responsible AI in Evidence Synthesis (RAISE): guidance and reco...

OSF Storage (Germany - Frankfurt)

Responsible AI in Evidence Synthesis v0.9.pdf

2024-09-10 09:25 PM

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were applied to remove records.

If machine learning algorithms were used to prioritise screening (whereby unscreened records were ordered based on screening decisions), state the software used and provide details of any software used (for example, screening stopped altogether leaving some records to be excluded, or screening switched from double to single screening once a pre-screened record was eliminated).

Selection process

Item 8. Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and, if applicable, details of automation tools used in the process

Data collection process

Item 9. Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and, if applicable, details of automation tools used in the process

Explanation: Authors should report the methods used to collect data from reports of included studies, to enable readers to assess the potential for errors in the data presented.

Essential elements

• Report how many reviewers collected data from each report, whether multiple reviewers worked independently (for example, data collected by one reviewer and checked by another), and any processes used to resolve disagreements between data collectors.

• Report any processes used to obtain or confirm relevant data from study investigators (such as how they were contacted, what data were sought, and success in obtaining the necessary information).

AI

Cochrane

Cochrane has launched a new AI policy

DRAFT Version 3.1: 13 March 2026

Responsible use of AI in Evidence Synthesis (RAISE 2026) 3: selecting and using AI evidence synthesis tools

Contributing authors and other author details: as per recommendations paper ('RAISE 1')

How to cite

Thomas J, Hair K, Noel-Storr, A. et al. Responsible use of AI in evidence Synthesis (RAISE): selecting and using AI evidence synthesis tools (version 3.1; updated 13 March 2026). In: Open Science Framework (<https://osf.io/>). Washington DC: Center for Open Science. DOI 10.17605/OSF.IO/FWAUD (accessed XXX via <https://osf.io/cqa82>).

Responsible use of AI in Evidence Synthesis (RAISE 2026) 1: Recommendations for practice

Authors: James Thomas [1, 2], Kaitlyn Hair [1], Anna Noel-Storr [3], Michelle Angrish [2, 4], Edoardo Aromataris [5], Lisa Askie, [6], Rigmor C Berg [7, 8], Yuan Chi [9, 10], A Justin Clark [2, 11], Declan Devane [12], Emma McFarlane [13], Isabel Fletcher [14], Gerald Gartlehner [15, 16], Jonas Goretzko [17], Neal Haddaway [18], Raouf Hajji [19], Pawel Jemiotto [2, 20], Zoe Jordan [5], Justine Karpusheff [21], Isabel Kempner [22], Wojciech Kusa [2, 23], Claudia Lenkewitz [17], Biljana Macura [24, 25], Laurenz Mahlanza-Langer [26], Iain J Marshall [27], Joerg J Meerpohl [28, 29], Samer Mheissen [30], Jan Minx [31], Will Moy [32], Andrew A. Rooney [33], Ashrita Saran [34], Birte Snijlsteit [35], Rene Spijker [2, 36], Marion Spring [13], Vickie R. Walker [2, 33], Ella Fleming [3]

DRAFT FOR CONSULTATION AND REVISION Version 3. 13 March 2026

Responsible use of AI in Evidence Synthesis (RAISE 2026) 2: building and evaluating AI evidence synthesis tools

Contributing authors and other author details: as per recommendations paper ('RAISE 1')

How to cite

Thomas J, Hair K, Noel-Storr, A. et al. Responsible use of AI in evidence Synthesis (RAISE 2026): building and evaluating AI evidence synthesis tools (version 3; updated 13 March 2026). In: Open Science Framework (<https://osf.io/>). Washington DC: Center for Open Science. DOI 10.17605/OSF.IO/FWAUD (accessed XXX via <https://osf.io/cqa82>).

THE UNIVERSITY of ADELAIDE

Position statement on artificial intelligence (AI) use in evidence synthesis across Cochrane, the Campbell Collaboration, JBI and the Collaboration for Environmental Evidence 2025

Ella Flemyng, Anna Noel-Storr, Biljana Macura, Gerald Gartlehner, James Thomas, Joerg J. Meerpohl, Zoe Jordan, Jan Minx, Angelika Eisele-Metzger, Candace Hamel, Pawel Jemioło, Kylie Porritt, Matthew Grainger Authors' declarations of interest

Version published: 11 November 2025

<https://doi.org/10.1002/14651858.ED000178>



Key messages:

1. Evidence synthesis should use artificial intelligence (AI) tools.
2. Cochrane, the Campbell Collaboration, JBI and the Collaboration for Environmental Evidence have developed a framework for evidence synthesis ecosystem.
3. Evidence synthesists developing and producing evidence synthesis reports should ensure that AI use does not compromise the methodological rigour of the synthesis.
4. AI and automation in evidence synthesis should be used transparently and publicly available information to inform decisions about whether an AI system or tool could and should be used in evidence synthesis.
5. Any use of AI or automation that makes a synthesis report.
6. AI tool developers should proactively ensure their AI systems or tools adhere to the RAISE recommendations so we have clear, transparent and publicly available information to inform decisions about whether an AI system or tool could and should be used in evidence synthesis.

Based on RAISE, Cochrane's position statement outlines [four expectations for evidence synthesists using AI](#):

1. You are ultimately responsible for your research, including the decision to use AI and how it is used
2. You can use AI provided you can demonstrate it will not compromise the methodological rigour or integrity of your synthesis
3. AI use should be fully and transparently reported
4. AI should be used with human oversight

Expectations 1 and 2 are where you assess an AI tool to help make an informed decision on whether to use it. But what steps do you need to take to do that?



Table 2: The CESAR project's stopping boundaries and decisions rules for interim analyses

Performance metrics	Futility boundaries (point estimate)	Non-inferiority margins (Upper limit of 95% CI)*	Decision rules
Screening			
Sensitivity	<80%	<95%	Stop if either boundary is crossed
Specificity (for full-text screening only)	<50%	<60%	Stop if either boundary is crossed
Data extraction			
Sensitivity	<92%	<97%	Stop if either boundary is crossed
Major error proportion	>3%	>2%	Stop if either boundary is crossed
Usability			
System usability scale (score)	<57	<75	Stop if threshold is not met

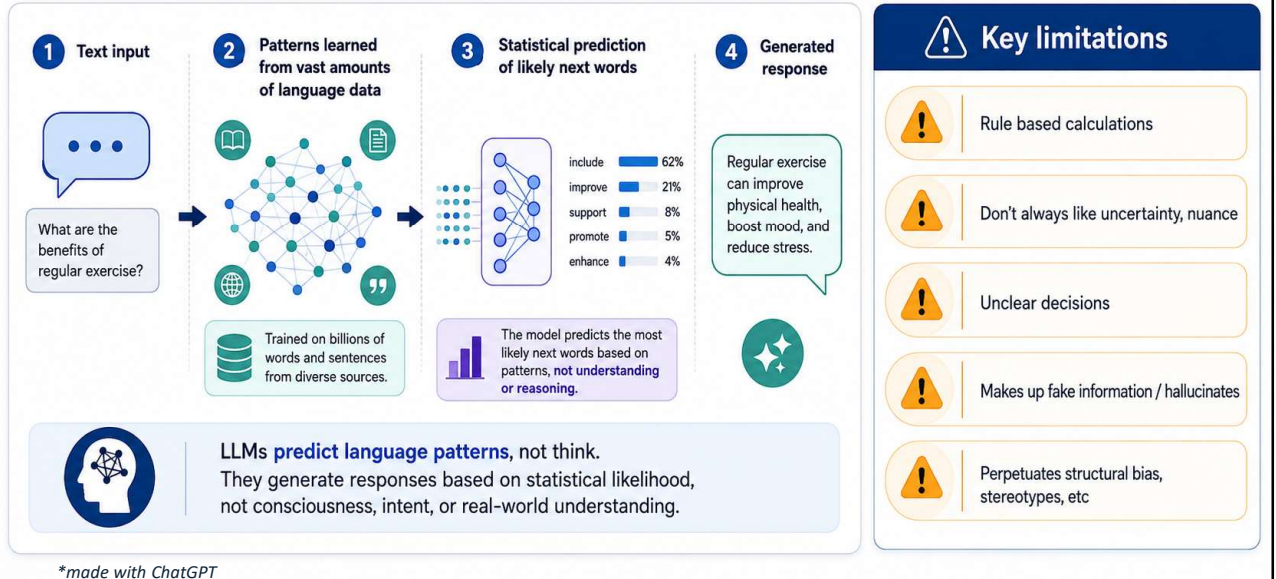
Right tool, right job: deciding when to not use an AI tool

What factors should you consider when deciding whether to use AI tools to support your work?

Monday, June 15, 2026 • By Ella Flemyng, Cochrane's Head of Editorial Policy and Research Integrity

How LLMs Work

Generative AI (LLMs) provide a statistical representation of language — in contrast to human reasoning



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If we use AI...

Summary Table of Common Parameters

Parameter	Goal	Lower Setting Behavior	Higher Setting Behavior
Temperature	Creativity/Randomness	Factual, repetitive	Creative, risky
Top-P (p)	Diversity of word choice	Limited, safe choices	Diverse, broad vocabulary
Top-K	Limit potential words	Highly restrictive	Broad, risky
Presence	Topic variety	Repetitive topics	Introduces new topics
Frequency	Sentence structure	Exact repetition	Varied phrasing

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Goal 	Temperature	Top-P	Penalty
Factual / Coding	Low (0.2)	Low (0.1)	Low
Standard Chat	Medium (0.7)	High (0.9)	Medium
Creative Writing	High (1.0+)	High (1.0)	High

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Task	Description	Classification
1. formulate review question	Decide on the research question of the review.	preparation
2. find previous SR	Search for SR that answers the same question.	
3. write the protocol	Provide an objective, reproducible, sound methodology for peer review.	
4. devise search strategy	Decide on databases and keywords to find all relevant trials.	
5. search	Aim to find all relevant citations even if many irrelevant ones included.	retrieval
6. de-duplicate	Remove identical citations.	
7. screen abstracts	Based on titles and abstracts, remove definitely-irrelevant trials.	appraisal
8. obtain full text	Download, request copies from authors, inter-library loans, etc.	
9. screen full text	Exclude irrelevant trials.	
10. snowball	Follow citations from included trials to find additional trials.	synthesis
11. extract data	Extract outcome numbers and associate with trial arm.	
12. synthesize data	Convert extracted data to common representation (usually average and SD).	
13. re-check literature	Repeat the search to find new literature published since the initial search.	
14. meta analyze	Statistically combine the results from all included trials.	write-up
15. write up review	Produce and publish the final report.	

Systematic review automation technologies

[Guy Tsafnat](#) , [Paul Glasziou](#), [Miew Keen Choong](#), [Adam Dunn](#), [Filippo Galgani](#) & [Enrico Coiera](#)

Systematic Reviews 3, Article number: 74 (2014) | [Cite this article](#)

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Automation and Machine Learning as a solution

6 Free Astonishing

!!!WARNING!!!

AI Tools for writing SYSTEMATIC REVIEWS
Dr. Imrah Qureshi, SPEAKER

CONNECTING Youtube
7 January 2023
8:00 PM Malaysia

Mushtaq Bilal, PhD
@MushtaqBilalPhD
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Most AI apps for academic research require a paid subscription. Not everyone can afford them.

So, team of researchers in Germany built ORKG. It's a free AI app you can use to supercharge your literature review.

Here's how to use it:
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AI Tools for Literature Reviews
App Toolkit for Modern Researchers

Knowledge Maps	Note-taking
Connected Papers Visual tool to help researchers find and explore related research papers. It uses machine learning to generate a network of related papers.	Glasp Web highlighter and annotation tool that helps organize literature from the web. It syncs across all devices and supports sharing.
Litmaps Online literature mapping tool that visualizes research trends and connections between papers.	SATRA Machine learning software for organizing and analyzing research papers and reporting them in a clear and concise manner.
Research Rabbit AI-powered research assistant that helps researchers find relevant papers and generate summaries.	Scite AI-powered citation analysis tool that helps researchers understand the impact of their research.
Paraphraser AI-based paraphrasing tool that helps researchers rewrite text in their own words.	Writing Assistant AI-powered writing assistant that helps researchers generate text and improve their writing.
Discovery AI-powered research discovery tool that helps researchers find relevant papers and generate summaries.	TRINKA AI-powered research assistant that helps researchers find relevant papers and generate summaries.
Scite AI-powered citation analysis tool that helps researchers understand the impact of their research.	jenni AI-powered research assistant that helps researchers find relevant papers and generate summaries.

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Automation tools to support undertaking scoping reviews

The International Collaboration for Automation of Systematic Reviews (ICASR) has put forward a set of principles for researchers to use automation for systematic reviews highlighting that automation has the potential to facilitate the production of systematic reviews that adhere to high standards for the reporting, conduct, and updating of rigorous reviews.

The Vienna Principles

1. Systematic reviews involve multiple tasks, each with different issues, but all must be improved.
2. Automation may assist with all tasks, from scoping reviews to identifying research gaps as well protocol development to writing and dissemination of the review.
3. The processes for each task can and should be continuously improved, to be more efficient and more accurate.
4. Automation can and should facilitate the production of systematic reviews that adhere to high standards for the reporting, conduct and updating of rigorous reviews.
5. Developments should also provide for flexibility in combining and using, e.g. subdividing or merging steps and allowances for different users to use different interfaces.
6. Different groups with different expertise are working on different parts of the problem; to improve reviews as a whole will require collaboration between these groups.
7. Every automation technique should be shared, preferably by making code, evaluation data and corpora available for free.
8. All automation techniques and tools should be evaluated using a recommended and replicable method with results and data reported.

ICASR

International Collaboration for the Automation of Systematic Reviews



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SR tools, automation, streamlining



Journal of Clinical Epidemiology 138 (2021) 80–94

ORIGINAL ARTICLE

Systematic review automation tools improve efficiency but knowledge impedes their adoption: a survey

Anna Mae Scott^{a,*}, Connor Forbes^a, Justin Clark^a, Matt Carter^a, Paul Zachary Munn^b

^a Institute for Evidence-Based Healthcare, Bond University, Gold Coast, Australia
^b JBI, Faculty of Health and Medical Sciences, The University of Adelaide, Adelaide, Australia
 Accepted 30 June 2021; Available online 7 July 2021

Abstract

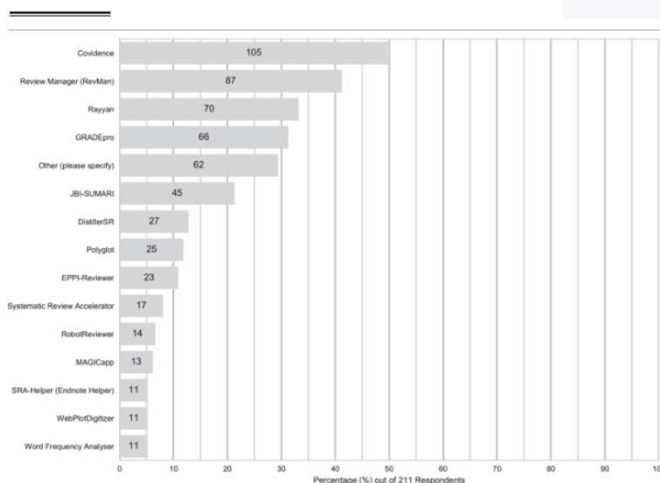
Objective: We investigated systematic review automation tool use by systematic reviewers, health technology assessment and guideline development organizations.

Study design and setting: An online, 16-question survey was distributed across several evidence synthesis assessment and guideline development organizations. We asked the respondents what tools they use and abandon, do they use the tools, their perceived time savings and accuracy, and desired new tools. Descriptive statistics results.

Results: A total of 253 respondents completed the survey; 89% have used systematic review automation whilst screening (79%). Respondents' "top 3" tools included: Covidence (45%), RevMan (35%), Rayyan and most commonly abandoned were Rayyan (19%), Covidence (15%), DistillerSR (14%) and RevMan (13%). Too increased accuracy (54%). Respondents taught themselves to how to use the tools (72%); lack of knowledge barrier to tool adoption (51%). New tool development was suggested for the searching and data extraction stages.

Conclusion: Automation tools will likely have an increasingly important role in high-quality and timely reviews required in training and dissemination of automation tools and ensuring they meet the desirable features of those reviews. © 2021 Elsevier Inc. All rights reserved.

Keywords: Automation; Automation tools; Systematic review; Systematic review automation; Health technology assessment; Clinical practice guideline



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Table 2. Speed and accuracy improvement from automation tool use

How much time do these tools save?

Time saved	N (%) of 184 responses
Saves a lot of time	67 (36%)
Saves some time	81 (44%)
Neutral	28 (15%)
Costs some time	6 (3%)
Costs lots of time	2 (1%)

Do the tools improve the accuracy of the systematic review/HTA/CPG?

Accuracy	N (%) of 185 responses
A lot of improvement in accuracy	50 (27%)
A little improvement in accuracy	50 (27%)
Neutral	82 (44%)
Lose some accuracy with using the tools	3 (2%)
Lose a lot of accuracy with using the tools	0 (0%)

Abbreviations: HTA, health technology assessment; CPG, clinical practice guideline.



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Table 3. Factors preventing respondents from using the automation tools

What prevents respondents from using the automation tools	
Factors	N (%) of 196 responses
The learning curve (too complicated to learn)	76 (39%)
Time constraints	55 (28%)
Costs	88 (45%)
Language barrier	5 (3%)
Internet connectivity/firewall	5 (3%)
User unfriendly	49 (25%)
Lack of knowledge of existing tools	100 (51%)
Not applicable	20 (10%)
Other (optional: please share why)	43 (22%)



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METHODOLOGY PAPER

Are systematic review and guideline development tools useful? A Guidelines International Network survey of user preferences

Zachary Munn PhD, GradDip HthSc, BMedRad,¹ Linn Brandt MD,² Ton Kuijpers PhD,³ Craig Whittington PhD,⁴ Louise Wiles PhD, BPhysio,^{5,6,7} Torsten Karge^{8,9}, on behalf of the G-I-N Tech Working Group
¹Faculty of Health and Medical Sciences, JBI, The University of Adelaide, Adelaide, South Australia, Australia; ²Department of Medicine, Irvin Hospital, Trondheim, Norway; ³South College of General Practitioners, Utrecht, The Netherlands; ⁴Doctor Evidence, Santa Monica, California, USA; ⁵Australian Centre for Precision Health, School of Health Sciences, University of South Australia, Adelaide, South Australia; ⁶Faculty of Medicine and Health Sciences, Centre for Healthcare Resilience and Implementation Science, Australian Institute of Health Innovation, Macquarie University, Sydney, New South Wales, Australia; ⁷South Australian Health and Medical Research Institute (SAHMRI), Adelaide, South Australia; ⁸Clinical Guideline Services, and ⁹Medical Department I (Gastroenterology, Infectiology, and Rheumatology), Charité – Universitätsmedizin, Berlin, Germany

ABSTRACT

Background: There are now over 140 tools/programs that can assist in developing systematic reviews or clinical practice guidelines (CPGs). It is currently unclear which tools are used by systematic reviewers and CPG developers, which development processes they are used for, and what facilitators or barriers to their use exist.

Methods: To determine which tools are currently being used by systematic reviewers and CPG developers, an online survey was administered during July–August 2017. Guidelines International Network individual and organizational members were invited to participate. Survey questions focused on the nature and frequency of members' use of tools to support systematic review and CPG development.

Results: The overall response rate was 34%. The largest number of respondents developed one to five guidelines a year (48%). GRADEpro GDT was the most popular tool (26% of respondents) followed by Dropbox (16%) and RevMan (14%). From the options provided, the reason most respondents (85%) used particular tools was 'to be more efficient'. Most users stated they would use the tool again (95%), and 95% would recommend it to other organizations. However, respondents reported that tool efficiency and facilitators such as data sharing functionality were offset by their availability and cost, issues with structured data fields (that did not allow customization), and other technical and usability factors (e.g., features, workflows).

Conclusions: The results of this survey provide a focus for discussing improvements in tools to meet the needs of systematic reviewers and CPG developers, and a basis from which to test the efficacy and appropriateness of various tools and platforms across a number of purposes and contexts.

Key words: guidelines, Guidelines International Network, systematic review, technology

JBI Evid Implement 2020; 18:345–352.

Research highlights

- There are many different tools available to assist with the conduct of systematic reviews and guidelines.
- The survey identified the most commonly used tools among members of an international network (Guidelines International Network) and how frequently they are used.
- Barriers to using tools include the cost of some tools, lack of customization and lack of features.
- Facilitators for using tools included improving the efficiency of the process, ability to share data/information, and being free to use.

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 DOI: 10.1097/XEB.0000000000000226

Background

Systematic reviews, and the recommendations or clinical practice guidelines (CPGs) arising from them, form the basis of evidence-based healthcare. Over time, systematic review and guideline development methods have become increasingly demanding and complex. As such, the development of systematic reviews and trustworthy CPGs require significant investment of resources, with systematic reviews alone taking anywhere from 6 months to 2 years to complete,^{1–3} with an average development time of 67.3 weeks shown in one study.⁴ With the need to provide up-to-date and trustworthy recommendations in clinical practice, this

Tool name ^a	Users
GRADEpro	23
Dropbox	14
RevMan	12
Other tool	11 ^b
Covidence	8
No online tool	8
MAGICapp	7
Rayyan	6
Google docs	6
PEER	5
DistillerSR	4
Team collaboration tools	4 ^c
Clinical guideline services	2
EPPI Reviewer	2
DECIDE Tools (via epistemonikos)	1
GROWTH DOC Library/DOC Data	1
JBI SUMARI	1
Abstrackr	1
Box	1
Microsoft Sharepoint	1

^aNo respondents reported using the following tools: Can Implement, Systematic Review Data Repository, and CREBP Review assistant.

^bEndnote 4, SurveyMonkey 2, AGREE or AGREE-II 3, Web based forum 1, SIGN Evidence Management System 1.

^cProjectplace, Zoho, Basecamp, Customised guidelines wiki.



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Levels of automation

Level 1: tools to improve the file management process such as citation databases, reference management software and systematic review management software.

Level 2: tools to enable workflow prioritisation such as prioritisation of relevant abstracts.

Level 3: tools used to perform a task automatically but unreliably and require human supervision or otherwise provide the option to override the tools decisions manually.

Level 4: tools that eliminate the need for human participation altogether.

A question of trust: can we build an evidence base to gain trust in systematic review automation technologies?

Annette M. O'Connor , Guy Tsafnat, James Thomas, Paul Glasziou, Stephen B. Gilbert & Brian Hutton

Systematic Reviews, 8, Article number: 143 (2019). | [Cite this article](#)

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TABLE 1 Tasks of a scoping review and how automation tools could support their efficiency.

Scoping review task	Method used	Suggested automation tools to increase efficiency or gain	Level of automation	Availability of the tool (open access/proprietary)
Team establishment	Personnel needed for the completion of the review	Crowd sourcing or using task sharing platforms i.e., JBI SUMARI and Covidence. Management teams—Trello	Level 1	Proprietary
Protocol development	Templated reports of some report items	JBI SUMARI and Revman	Level 1	Proprietary
Searches	Running searches on databases	Automatic alerts from databases. Database (i.e., Cochrane, JBI and Campbell, Health Database Advanced Search (HDAS)) Automatic retrieval of full-text papers (e.g., CrossRef), Polyplot Search Translator Litsuggest, eSuRPr	Level 4	CrossRef and Litsuggest (Open access) The rest of the tools are proprietary.
Deduplication	Deleting duplicates	Endnote, Systematic Review Accelerator (SRA De-duplicate), Abstrackr, Rayyan, EPPI-Reviewer, Deduklick, Covidence and DistillerSR.	Level 3	Abstrackr (Open access) Rayyan (Open Access to early career researchers) The remainder of tools are proprietary.
Screening	Selecting studies for inclusion	Crowdsourced inclusion decision and machine learning classifier (Abstrackr, Rayyan, BIBOT, EPPI-Reviewer, ASReview and DistillerSR). Covidence is also used for this step.	Level 2	Abstrackr (Open access) Rayyan (Open Access to early career researchers) The remainder of tools are proprietary.
Data extraction	Extracting information on participants, Concept and context	Machine learning-information extraction systems such as DistillerSR and ExaCT), Tabulizer, UDPipe, Webplotdigitizer. For non-machine learning but wanting a faster extraction process- Covidence	Level 4	UDPipe (open access) and the remainder of the tools are proprietary.
Data charting	Presentation of data	GoogleCharts, Tableau Public, Google Data studio, Drawio, Eppi- reviewer, NVivo.	Level 1	Googlecharts, Google data studio and Drawio (open access). The remainder of the tools are proprietary.
Report writing	Templated reports of some report items	JBI SUMARI, Revman and Robotreviewer	Level 1	Proprietary

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ABSTRACT
Background An overview of the research. How research output systematic review intelligence (AI) this communication transparent and tool 'ASReview' **Methods** Use First, the tool re several prela

The reviewer of

checking for ini
stopping criteri

BACKGROUND
Medical-science

BACKGROUND
Medical-sci

METHODOLOGICAL REVIEW Open Access

How to optimize the systematic review process using AI tools

Nicholas Fabiano, Arnav Gupta, Nishaant Bhambra, Brandon Luu, Stanley Wong, Muhammad Maaz, Jess G. Fiedorowicz, Andrew L. Smith, Marco Solmi 

First published: 23 April 2024 | <https://doi.org/10.1002/jcv2.12234>

Nicholas Fabiano, Arnav Gupta and Nishaant Bhambra contributed equally to this paper.

SECTIONS

PDF TOOLS SHARE

Abstract

Systematic reviews are a cornerstone for synthesizing the available evidence on a given topic. They simultaneously allow for gaps in the literature to be identified and provide direction for future research. However, due to the ever-increasing volume and complexity of the available literature, traditional methods for conducting systematic reviews are less efficient and more time-consuming. Numerous artificial intelligence (AI) tools are being released with the potential to optimize efficiency in academic writing and assist with various stages of the systematic review process including developing and refining search strategies, screening titles and abstracts for inclusion or exclusion criteria, extracting essential data from studies and summarizing findings. Therefore, in this article we provide an overview of the currently available tools and how they can be incorporated into the systematic review process to improve efficiency and quality of research synthesis. We emphasize that authors must report all AI tools that have been used at each stage to ensure replicability as part of reporting in methods.

Automation tools to support undertaking scoping reviews

Hanan Khalil Danielle Pollock, Patricia McInerney, Catrin Evans, Erica B. Moraes, Christina M. Godfrey,

First published: 17 June 2024 | <https://doi.org/10.1002/jrsm.1731>

SECTIONS

PDF TOOLS SHARE

Abstract

Objective

This paper describes several automation tools and software that can be considered

[Home](#) > [Computing](#) > [Article](#)

Artificial intelligence to automate the systematic review of scientific literature

Regular Paper | [Open access](#) | Published: 11 May 2023
Volume 105, pages 2171–2194, (2023) | [Cite this article](#)Download PDF You have full access to this open access articleJosé de la Torre-López, Aurora Ramírez  & José Raúl Romero

17k Accesses 15 Citations 11 Altmetric Explore all metrics →

Abstract

Artificial intelligence (AI) has acquired notorious relevance in modern computing as it effectively solves complex tasks traditionally done by humans. AI provides methods to represent and infer knowledge, efficiently manipulate texts and learn from vast amount of data. These characteristics are applicable in many activities that human find laborious or

TABLE 1	AI tools to optimize the sustainable review process
1	AI-powered literature screening tools (e.g., Elicit, Scisearch, Semantic Scholar) to quickly identify relevant papers based on keywords and abstracts.
2	AI-driven text analysis tools (e.g., NVivo, ATLAS.ti) to extract key themes and concepts from large volumes of text.
3	AI-powered citation analysis tools (e.g., CiteSpace, Gephi) to map research trends and identify influential papers.
4	AI-driven sentiment analysis tools (e.g., Lexalytics, MonkeyLearn) to assess the tone and sentiment of research findings.
5	AI-powered plagiarism detection tools (e.g., Turnitin, iThenticate) to ensure the originality of research papers.
6	AI-driven recommendation systems (e.g., ResearchGate, Scopus) to suggest relevant papers and research areas.
7	AI-powered data visualization tools (e.g., Tableau, PowerBI) to present research findings in a clear and concise manner.
8	AI-driven language translation tools (e.g., Google Translate, Bing) to facilitate the review of research papers in different languages.
9	AI-powered research funding tools (e.g., GrantWatch, FundingCentral) to identify potential funding opportunities.
10	AI-driven research collaboration tools (e.g., ResearchHub, ResearchGate) to connect researchers and facilitate collaboration.

Section	AI tool	URL	Description
Abstract	Graphical Abstract Maker	https://mindthegraph.com/app/graphical-abstract-maker	<ul style="list-style-type: none">• Simplifies complex research into understandable visuals.
Introduction	Elicit.org	https://elicit.org/	<ul style="list-style-type: none">• Assists in formulating well-thought research questions during the early phases of a systematic review which can help to brainstorm a research question.
	OpenAI ChatGPT	https://chat.openai.com/	<ul style="list-style-type: none">• Refines research questions by providing diverse perspectives and structured approaches, enhancing the brainstorming process.• Summarizes raw data into concise, meaningful abstracts, thus saving time.
	ForeFront AI Chat	https://chat.forefront.ai/	<ul style="list-style-type: none">• Helps in structuring the introduction by generating suggestions based on provided information.
	SciEe.al	https://sciee.al	<ul style="list-style-type: none">• Allows the creation of unique writing personas and writing voices, enhancing the manuscript's style and tone.
	Jenni.ai	https://jenni.ai	<ul style="list-style-type: none">• Finds citations related to GPT-generated responses, allowing for the user to find relevant sources to cite.
	Research Rabbit App	https://researchrabbittapp.com/	<ul style="list-style-type: none">• Facilitates the writing process by offering prompts and suggesting text, thereby making it easier to write the rationale.
	Consensus.app	https://consensus.app	<ul style="list-style-type: none">• Suggests related papers based on Zotero saved ones, promoting thorough research for the rationale.
	EvidenceHunt	https://evidencehunt.com/	<ul style="list-style-type: none">• Simplifies the research process by summarizing top papers and consensus from the scientific community, which can be used in the rationale.
Methods	LitSuggest	https://www.ncsl.nm.nih.gov/research/litsuggest/	<ul style="list-style-type: none">• Generates answers with cited articles, facilitating a swift and efficient research process for the rationale.
	PaperDigest	https://www.paperdigest.org/	<ul style="list-style-type: none">• Recommends similar studies based on your research interest using machine learning.
			<ul style="list-style-type: none">• Assists in building a solid literature review on any topic, providing a strong foundation for the rationale of the study and existing state of the literature.
	Distiller SR	https://www.distillerai.com/products/distiller-sr-systematic-review-software	<ul style="list-style-type: none">• A validated AI tool performs literature screening after training on a proportion of his.
	Xtrc	http://xtrc.ai	<ul style="list-style-type: none">• Employs semantic search to filter for eligibility criteria, thereby enhancing study selection efficiency.• Finds at least five articles for MeSH terms, facilitating a targeted and specific search strategy.
	WiseOne.io	https://app.wiseone.io/	<ul style="list-style-type: none">• Ensures information reliability by presenting various sources discussing the same subject.
	SearchSmart	https://www.searchsmart.org/	<ul style="list-style-type: none">• Assists in selecting the best research database, maximizing the relevance and quality of search results.
	CitationChaser	https://reethc.shinyapps.io/citationchaser/	<ul style="list-style-type: none">• Identifies relevant research topics by tracing citation networks, thus expanding the scope of the search strategy.
	Consensus.app	https://consensus.app	<ul style="list-style-type: none">• Searches for relevant literature based on any question, providing a thorough research foundation.

TABLE 2 Correlation matrix of tools and respective manuscript sections.

	Protocol	Screening/data extraction		Manuscript					
Tools	Research question	Search key	Screening	Data extraction	Introduction	Abstract	Methods	Results	Discussion
ChatPDF							✓	✓	
CitationChaser		✓					✓		✓
Consensus.app							✓		✓
Covidence			✓						
Distiller SR			✓						
Elicit.org					✓				
EvidenceHunt					✓				
ForeFront AI Chat					✓				✓
Graphical Abstract Maker						✓			
HoyGPT.Chat							✓	✓	
Humata.ai							✓	✓	
Jenni.ai					✓				✓
LitSuggest					✓				
OpenAI ChatGPT	✓				✓	✓	✓	✓	
PaperDigest		✓			✓		✓		
PDFGear							✓	✓	
Rayyan.ai		✓					✓		
RCT Tagger							✓	✓	
Research Rabbit App					✓				
RobotReviewer							✓	✓	
Scholarcy									✓
Scite.ai					✓				✓
SearchSmart							✓		
Thalia		✓					✓		
WiseOne.io		✓					✓		
Xtrct		✓	✓				✓	✓	



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- Current approaches to evidence syntheses and changes during the pandemic 24
- Challenges of conventional literature review 24
- Extent of the use of automation 25
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- Advantages of using automated approaches to conduct evidence syntheses 26
- Reduction in burden 26
- Ease of use 26
- Enables completion of new tasks 27
- Challenges and needs in using automation for evidence syntheses 27
- Continued need for human input 27
- Technical limitations 27
- Need for staff training and capacity 28
- Cost and equipment/resource requirements 28
- Lack of trust and performance evaluation 28
- Factors that can support the use of automation 29
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Results

Based on the qualitative data collected from EU/EEA public health bodies participating in this study, we found that automated technology is used to a limited extent for conducting evidence synthesis, with most participants not currently using these types of tools. This may be because they do not conduct any type of review within their organisation (instead, relying on reviews produced by others) or because of different challenges and obstacles that can arise when attempting to use automated approaches (discussed below). However, there were a few public health bodies that used automated tools, sometimes extensively. Among these public health bodies, technologies were used in different stages of the evidence synthesis process, although they seem to be particularly used to semi-automate the screening stage of reviews. For other public health bodies, the adoption of new technologies was being explored for the future.

Use and impact of new technologies for evidence synthesis

Literature review and qualitative data collection

2022 (Disclosure: I was a survey participant)





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Key Question (KQs)

KQ 1: What tools that use artificial intelligence (AI) or machine learning (ML) to semi- or fully automate any aspect of evidence synthesis product (ESP) production have had their performance evaluated?

KQ 1a: How do these tools perform?

Research Protocol | nph 127, 2024

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MACHINE LEARNING





Systematic Reviews 11, Article number: 258 (2022) | [Cite this article](#)



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From:
Date: 17 June 2026 at 10:16:17 am AEST
To: Zachary Munn
Subject: evidence synthesis perspective

CAUTION: External email. Only click on links or open attachments from trusted senders.

Hey Zachary,

You run HESRI at Adelaide Uni, so you've probably seen the full range of systematic reviews across health. We built an AI platform for SRs and validated it against Cochrane (published on medRxiv), but I'm sure there are gaps only someone with your experience would catch.

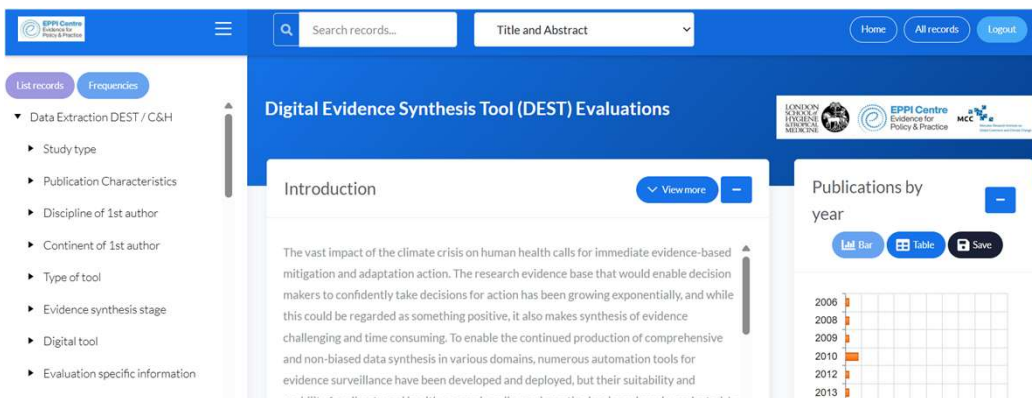
Your role as director of evidence synthesis means you think about the whole process, not just one step. I'd love to hear your honest take on where AI could actually help (and where it can't). Would you be up for a quick chat sometime?



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Digital Evidence Synthesis Tools (DEST)

<https://eppi.ioe.ac.uk/eppi-vis/Frequencies/GetMapById>



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Critical questions to ask when considering using a new tool for evidence synthesis

Slide from a presentation by James Thomas:

<https://eppi.ioe.ac.uk/CMS/Portals/0/ARC%20masterclass%20on%20AI%20for%20web2.pdf>



Does it enable me to draw on the sum of current knowledge?

Or does it present an incomplete or biased picture?



Does it enable me to distinguish between reliable and unreliable research?

Or does it treat all research as equally reliable?



Is the tool itself reliable?

Do we know how it works? Is it validated for my use case?

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Automation tools to support undertaking scoping reviews

The International Collaboration for Automation of Systematic Reviews (ICASR) has put forward a set of principles for researchers to use automation for systematic reviews highlighting that automation has the potential to facilitate the production of systematic reviews that adhere to high standards for the reporting, conduct, and updating of rigorous reviews.

The Vienna Principles

1. Systematic reviews involve multiple tasks, each with different issues, but all must be improved.
2. Automation may assist with all tasks, from scoping reviews to identifying research gaps as well protocol development to writing and dissemination of the review.
3. The processes for each task can and should be continuously improved, to be more efficient and more accurate.
4. Automation can and should facilitate the production of systematic reviews that adhere to high standards for the reporting, conduct and updating of rigorous reviews.
5. Developments should also provide for flexibility in combining and using, e.g. subdividing or merging steps and allowances for different users to use different interfaces.
6. Different groups with different expertise are working on different parts of the problem, to improve reviews as a whole will require collaboration between these groups.
7. Every automation technique should be shared, preferably by making code, evaluation data and corpora available for free.
8. All automation techniques and tools should be evaluated using a recommended and replicable method with results and data reported.

ICASR

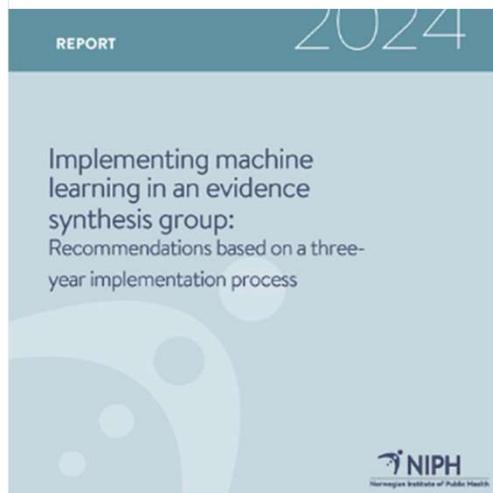
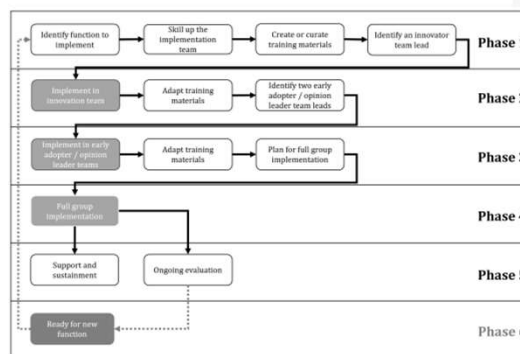
International Collaboration for the Automation of Systematic Reviews



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This report provides recommendations on how to carry out implementation of ML functions in ML-naïve evidence synthesis groups, based on the experiences implementing ML at HTV. It offers "best practice" suggestions, rooted in our reflections on implementation, aiming to assist other ML naïve groups or institutions in implementing ML functions in the evidence synthesis process. The guide is adaptable to different organizational goals and objectives, while providing insights applicable to implementation of various ML tools and functions.

The report is structured into three main sections corresponding to different phases of implementation: pre-implementation, implementation, and sustainment/evaluation. We use the EPIS framework throughout the document as a tool to explain the different implementation phases and important aspects to consider in each phase. Each section concludes with a "Take home message" based on our implementation experiences, summarized as practical tips on important aspects that we believe are important to consider in the implementation process.



Developing guidelines is a human endeavour

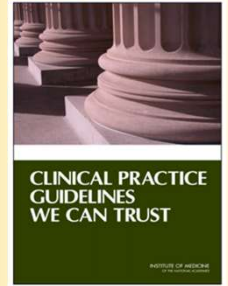
Guidelines



Clinical practice guidelines are statements that include recommendations intended to optimize patient care that are informed by a **systematic review** of evidence and an assessment of the **benefits and harms** of alternative care options.



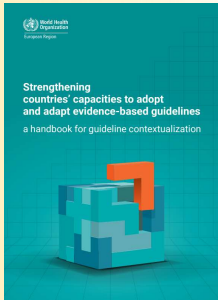
(Institute of Medicine, 2011)



Trustworthy guidelines are the cornerstone of giving evidence-informed advice in response to clinical, public health and health policy questions. They address those questions by using the **best available evidence** and transparently integrating the **judgements of experts** and the **input of stakeholders** in the process



(WHO Handbook for guideline contextualization, 2023)



How AI works

Generative AI (LLMs) provide a statistical representation of language – in contrast to human reasoning

Rule based calculations

Don't always like uncertainty, nuance

Unclear decisions

Makes up fake information/hallucinates

Perpetuates structural bias, stereotypes, etc

In guidelines:

Evidence AND value based judgements

Conscious dealing with uncertainty, conflicting results, trade offs

Referencing, cited and transparent decisions

Acknowledge and integrate different perspectives

Recognise importance of human connection, patients as persons, lived experience

Why Human Researches are Irreplaceable?



Slide courtesy of Valentin III Dones from GES*

*Note appropriate recognition of borrowed ideas

What if we do it once and do it right

Computable data

RoB

Results data coded

All EtD criteria coded and available

SRDR, Cochrane database, FEVIR, ALIVE, ESIC

Evidence inventories/registries, recommendation maps, adolopment

The future.....

Never a better time for automation in evidence synthesis due to:

- Open science and reusable data
- Modern technology
- Advances in AI
- Tech literacy
- Sharing and collaboration
- Interoperability and common standards
- Societal needs and pressures requiring innovation

Never a worse time for automation in evidence synthesis due to:

- Contributing to more poor quality reviews
- Competition
- Risks of AI not being addressed
- Tools appearing and disappearing
- Societal pressures leading to shortcuts
- Lack of commitment to common standards

Where does this leave us?

Lots of hype but not sure all applications 'stack up'

Everyone is looking for an easy answer – I don't think it exists (yet)

Personally – more trust in credible, evidence synthesis specialist organisations/collaborations – i.e. Covidence, Eppl-Reviewer, SR Accelerator, MAGICapp, GRADEPro

Less likely to disappear and more likely to be maintained – or provide support

These will make improvements and save time – but may not be 'game changing'

....we need a living evidence review on SR automation tools (plus evaluations) to underpin a resource such as the SR toolbox or ICASR repository (and collaboration in tool development)

Ensuring high quality and efficient development of trustworthy guidelines

Planning and production - GIN McMaster checklist

GRADE

Handbooks and guidance – NHMRC, GRADE

Reporting standards – RIGHT

RIGHT
Reporting Items for Practice Guidelines in Healthcare

Evaluate trustworthiness of a guideline – AGREE

AGREE II
M Authoring & Publication Platform

Software – MAGICApp, GRADEPro, Covidence

covidence

Networking, registering guidelines, collaboration - GIN

GIN
Guidelines International Network

GIN Public

Adapt and adopt – GRADE Adolopment

Engagement with community – MuSE/ GIN Public



MuSE

For education and training – INGUIDE

INGUIDE
International Guideline Development
Credentialing & Certification Program



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Concluding thoughts

No single AI/ML software solution – yet(?)

Consider evidence synthesis type, scope, restrictions

AI (and computable evidence) will likely let us do synthesis ‘at the push of the button’ or a form of it at some stage

Guidelines still require the human touch

Need to consider people, processes, technology

Need to invest in training and upskilling

Build efficient workflows for different projects through testing and refinement

Consider other approaches to improve efficiency (living, mapping, adolopment, updating, centralised registry, collaboration [built on FAIR/open science/standards for interoperability])

We have come a long way (paper, manual referencing, excel, no interoperability)– **but** still have further to go!



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Evidence Synthesis Taxonomy Initiative [↗](#)

Supporting researchers to conduct the right review, for the right reasons, with the right methods.

[Find out more](#) [↗](#)

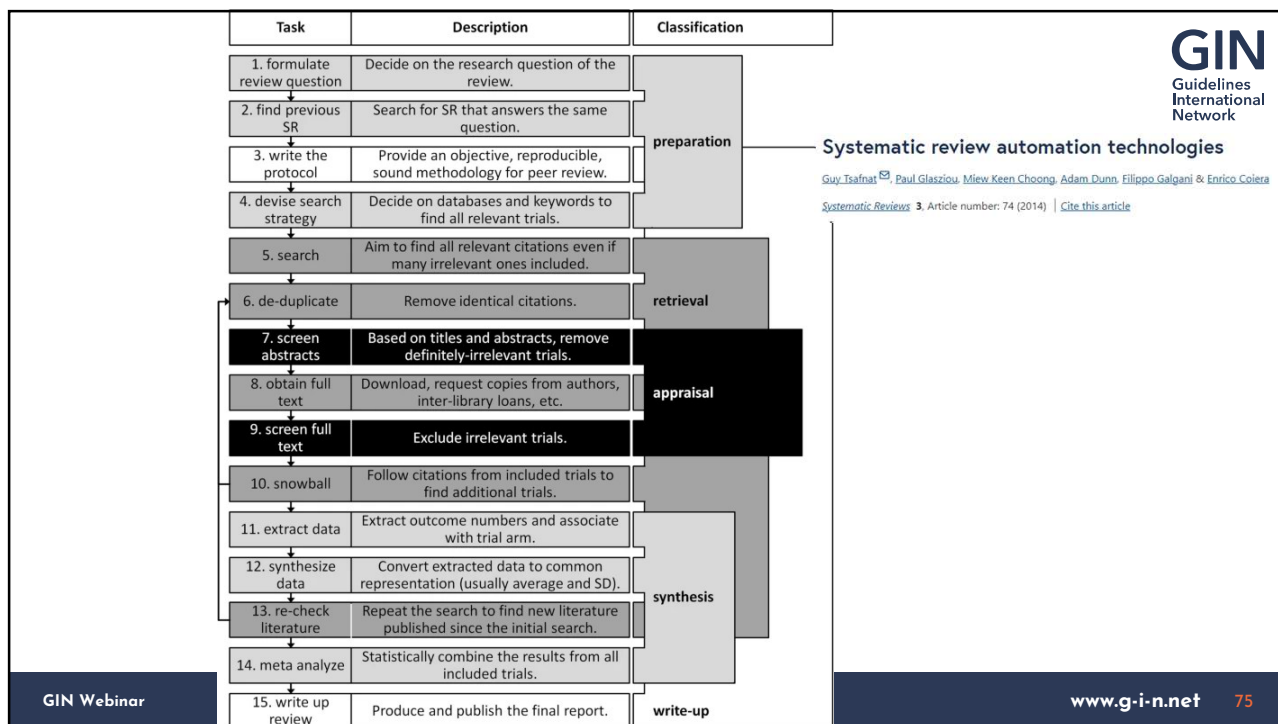
Right Reviews Right Reasons Right Methods

ChatGPT/ Claude AI

When does it work? How do we use it?

- Background and discussion ideas
- Risk management/project management plans
- Consider coverage of all knowledge, credibility of knowledge
- Suggested text for some methods sections
- Ideas on risk of bias/ appraisal but not trustworthy (*Claude impressive*)
- Search term generation/ search strings (but not trustworthy)
- R code (?)
- Plain language summary/ executive summary

- What will it be able to do in the future? Will this be the 'game changer'?



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Workflows: SR of RCTs

Protocol: Templates – SUMARI, RevMan or methods wizard

Searching: Polyglot search translator, Citation chaser/SpiderCite, Co-cites, De-duplicator, Endnote

Screening: Covidence (including RCT classifier)

Extraction: Covidence

RoB: Covidence, RoB excel

Analysis: RevMan

Write up: Word, endnote, Revman

Certainty of findings: GRADEPro

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Workflows: Scoping Review/Evidence Maps

Protocol: Templates, SUMARI

Searching: Polyglot search translator, Citation chaser/SpiderCite, Co-cites, De-duplicator

Screening: Covidence/Eppi-Reviewer

Extraction: Covidence/Eppi-Reviewer

RoB: NA

Analysis/Presentation: Covidence/Eppi-Reviewer/Eppi-Mapper/Eppi-Visualiser/Nvivo

Write up: Word, endnote

Certainty of findings: NA

Workflows: Guidelines

As above, but also:

Facilitate report writing, publishing, living mode: MAGICapp

Panel voting, judgements, reviewing: GRADEPro, MAGICapp

Automatically generated shared decision making tools: GRADEPro, MAGICapp