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HELPDESK RESPONSE 183

Using AI to Automate The Literature Review Process in Education:

A Topic Brief

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Please also note that this topic brief is set in the context of EdTech Hub's prior work, and, therefore, also includes several self-citations by the lead author, who also serves as technical director of EdTech Hub.

Reviewers

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EdTech Hub is a global research partnership. Our goal is to empower people by giving them the evidence they need to make decisions about technology in education. Our evidence library is a repository of our latest research, findings and wider literature on EdTech. As a global partnership, we seek to make our evidence available and accessible to those who are looking for EdTech solutions worldwide.

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Abbreviations and glossary

This document avoids the use of abbreviations and acronyms as much as possible. Nevertheless, we have collated a short list of common acronyms which readers might encounter in the general literature pertaining to the topic at hand. The glossary was compiled using ChatGPT.

Glossary

AI (Artificial Intelligence): A branch of computer science that aims to create machines or systems capable of intelligent behaviour, simulating human cognitive processes.

AILR (AI-based Literature Reviews): AI-based Literature Reviews is a phrase coined by ⇡Wagner et al. (2022).

ANN (Artificial Neural Network): A computational model inspired by the structure and function of biological neural networks, used in machine learning to process information and make decisions.

API (Application Programming Interface): A set of rules and tools that allows different software applications to communicate with each other, enabling the exchange of data and functionality.

DL (Deep Learning): A subset of machine learning that involves neural networks with multiple layers (deep neural networks), allowing the model to learn complex representations of data.

Explainable AI (XAI): Explainable AI refers to artificial intelligence systems designed to make their decision-making processes understandable and transparent to humans. It involves methods and techniques that allow users to comprehend how and why an AI model arrives at specific conclusions or predictions, enhancing trust and accountability.

GPT (Generative Pre-trained Transformer): A type of artificial intelligence model that uses transformer architecture and is pre-trained on a large dataset to generate human-like text in a wide range of contexts.

Hallucination: In the context of AI, hallucination refers to instances where a model generates outputs that are not based on real or accurate information, often producing incorrect results.

Large Language Model (LLM): A Large Language Model refers to a type of artificial intelligence model that is designed to understand and generate human-like language based on the patterns it has learned from extensive amounts of textual data. These models are characterised by their large size, typically containing millions or even billions of parameters.

LDA (Latent Dirichlet Allocation): A statistical model used for topic modelling, which identifies topics within a collection of documents and assigns probability distributions to words in those topics.

ML (Machine Learning): A subset of artificial intelligence that focuses on developing algorithms and models that enable computers to learn patterns from data and make predictions or decisions without explicit programming.

NLG (Natural Language Generation): The process of generating natural language text or speech by a computer, often used in applications where human-like communication is required.

NLP (Natural Language Processing): A field of AI that focuses on the interaction between computers and human language, enabling machines to understand, interpret, and generate human-like text.

NLU (Natural Language Understanding): The ability of a machine to comprehend and interpret the meaning of human language, going beyond simple pattern recognition to understand context, semantics, and user intent.

RAG (Retrieval-Augmented Generation): RAG is a natural language processing (NLP) model that combines elements of both retrieval and generation in order to improve the quality and relevance of generated text.

Topic modelling: Topic modelling is a natural language processing (NLP) technique used to identify topics present in a collection of text documents. The primary goal is to discover hidden thematic structures within the text data, revealing patterns of co-occurring words that suggest the presence of specific topics or themes. One of the popular methods for topic modelling is Latent Dirichlet Allocation (LDA), though there are others like Non-Negative Matrix Factorization (NMF) and Latent Semantic Analysis (LSA).

Zotero: a free, open-source reference management tool that helps users collect, organise, cite, and share research

Additional abbreviations

CSV	Comma-separated value
EEF	Education Endowment Foundation
FCDO	Foreign, Commonwealth and Development Office
GUI	Graphical User Interface
LMIC	Low- and middle-income country
PICO	Population, intervention, context, and outcome)
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RCT	Randomised controlled trial
RIS	Research Information System
VAT	Value-added tax

1. Introduction

Systematic literature reviews are often conducted manually in many research organisations. This topic brief explores the use of AI to automate the literature review process in the field of EdTech in order to improve the speed and efficiency of creating literature reviews across the sector.

The topic brief is guided by the following questions, provided as part of the corresponding helpdesk request to EdTech Hub:

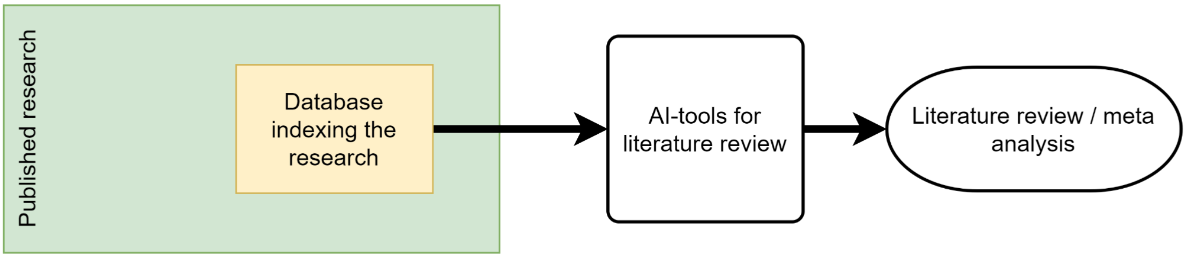
- What tools are available for organisations and projects (university-based research, research in intergovernmental organisations, donor-funded programmes, within the not-for-profit sector) to use to automate evidence reviews?
- How appropriate are existing tools? Are they easy to use? Do they have licensing or cost barriers? How advanced are these AI tools?
- What tools are other organisations using to present the best evidence quickly?
- Is there value in EdTech Hub building a bespoke AI tool to help identify, review, and synthesise evidence for literature reviews on education in low- and middle-income countries (LMICs)?
- What are the pros and cons of building a bespoke AI tool focusing on education in LMIC versus using an already existing commercial product? What are the cost implications of the two options?

2. Overview of findings

Several steps need to be undertaken to ensure a literature review is successful, as outlined below. In many of these steps, existing AI-based tools can make significant contributions. However, the fields of education and EdTech specifically (and the social sciences more broadly) face particular challenges around the availability of evidence.

To illustrate the challenges, Figure 2.1. illustrates a simplified literature review process. The green box indicates all published research in a specific field, with the yellow box indicating a database that covers part of that published research. This database is used by AI tools for literature reviews (the middle box), resulting in a literature review (or meta-analysis).

Figure 2.1. *Simplified literature review process*



2.1. AI tools for literature review

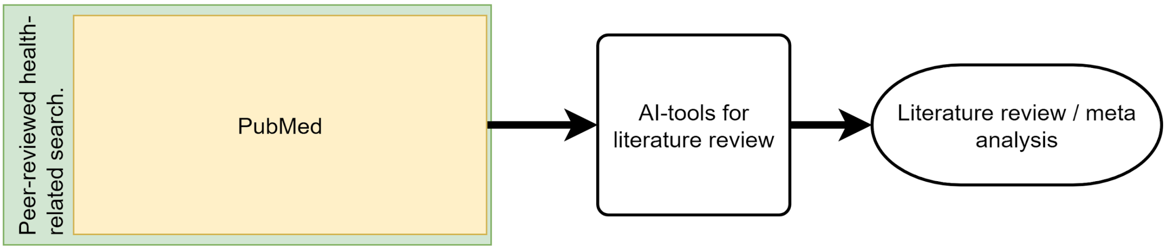
Many AI tools for literature reviews are currently available. They are at different stages of maturity and usability, but many show great promise.

However, it is important to note that AI is more commonly used in disciplines other than education (see the discussion in Section 3 on AI and literature reviews). Nonetheless, despite some specific features of education research, there is no reason to doubt that AI tools are just as applicable to education and EdTech research as they are to other fields.

2.2. Literature inputs

There are significant differences between published research in education/EdTech and other fields, such as health. In particular, there is a stark contrast in how research outputs are organised in education compared to health. In health research, some databases cover the vast majority of health-related research; this is partly because of the rigorous registration requirements for medical research (see Figure 2.2. below).

Figure 2.2. *Availability of evidence for health research*



However, there are no such stringent requirements for education research (e.g., for research registration) and no comprehensive databases. Moreover, grey literature, frequently not indexed at all, can often make significant contributions to education research. Figure 2.3. illustrates this, while Figure 2.4. demonstrates how this leads to divergent reviews

Figure 2.3. *Availability of evidence for education research*

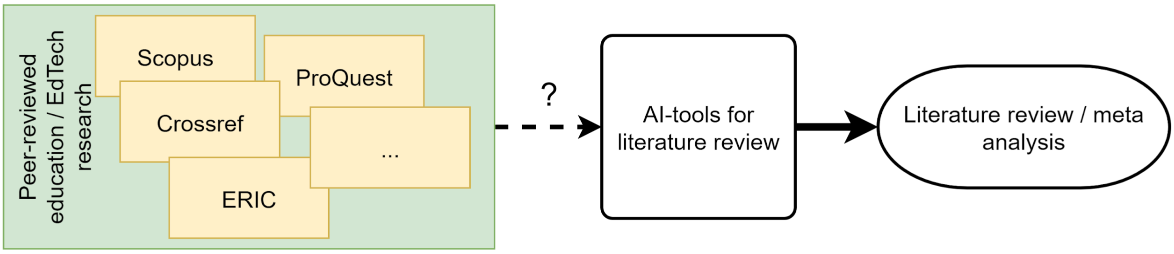
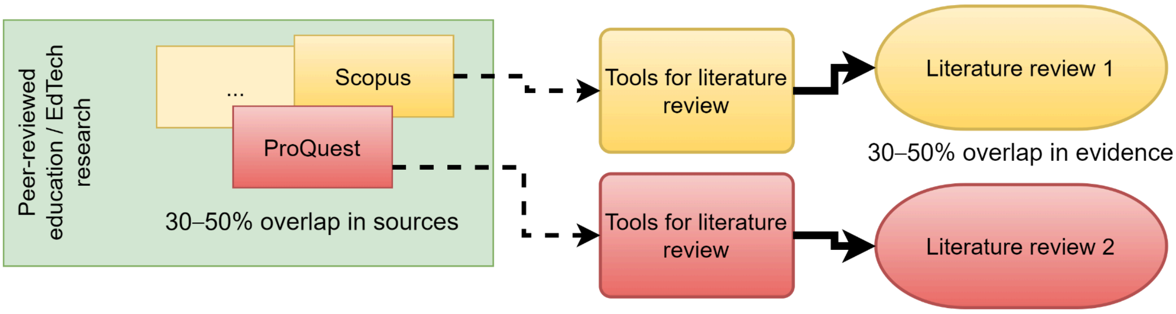


Figure 2.4. *The lack of a single database leads to divergent literature reviews and meta-analyses*



2.3. Questions posed for this topic brief

As noted above, most current uses of AI in research are in disciplines other than education; for example, where databases for easy-to-use AI tools can be determined, they turn out to be based on databases with poor coverage of education or EdTech (e.g., the Semantic Scholar database). Most easy-to-use AI tools, while applicable in principle to the field of education or EdTech (see Section 2.1 on AI tools for literature review), do not operate on databases that comprehensively index education/EdTech research;

therefore, in practice, these easy-to-use AI tools are not currently helpful to researchers in education/EdTech.

2.3.1. What tools to automate evidence reviews are available? Are they easy to use?

At the time of writing, no AI tools that are very easy to use or would support a comprehensive literature review from start to finish are available. Section 5 on integrated literature review tools discusses tools that offer support at all stages of the process. These tools are ↑EPPI-Reviewer (5.1.1.), ↑ASReview (5.1.2.), ↑DistillerSR (5.1.3.), and ↑Colandr (5.1.4.).

It is possible to use a variety of AI tools which support different steps of the literature review process; these are known as semi-integrated tools. ↑Iris.ai (5.2.1.), ↑Lateral.io (5.2.2.), ↑SciSpace (5.2.3.) and ↑Scanlitt (5.2.4.) are examples of semi-integrated tools and are discussed in further detail in Section 5.2.

Figure 4.1. in Section 4.2. further outlines the potential for AI support in the literature review process, identifying various web-based tools that could be used at each step, and their cost. Examples of AI tools that could be used for the literature review process, and mentioned in Figure 4.1., include, for example, tools for problem formulation (↑Elicit), literature search (↑LitSonar, ↑Elicit, ↑ORKG Ask, and ↑EPPI-Reviewer), screening for inclusion (↑ASReview, ↑Rayyan), quality assessment (↑RevMan, ↑RobotReviewer), data extraction (↑Elicit), and data analysis and interpretation (↑RevMan, ↑dmetar).

Web-based AI tools like ↑Elicit are useful for examining research questions quickly and without needing specialist knowledge; such tools often operate on a very limited selection of literature relevant to education and EdTech. Based on prior experiments, the fraction of literature covered may be 10% or less.

Such simple-to-use tools must be compared with established tools, e.g., ↑EPPI-Reviewer (which can also use the ↑OpenAlex dataset) and ↑ASReview. These established tools tend not to foreground their use of AI but nevertheless often incorporate powerful AI tools. Tools like ↑EPPI-Reviewer are not as simple to use as some available web-based tools; however, unlike web-based tools, they offer a significantly more rigorous and transparent approach. While using ↑EPPI-Reviewer involves a learning curve, the learning is appropriate to research-level use and aims, i.e., to generate best-evidence synthesis.

Many emerging web-based tools are aimed at a broader audience, perhaps including students and researchers examining topics casually. While some of these new tools may become major contenders for creating high-quality reviews, as things stand, tools like ↑EPPI-Reviewer will create more credible outputs. That is not to say that you should not consult web-based tools like Google Scholar; however, it is advisable to supplement such tools with other literature databases for rigorous work.

In addition to integrated tools, other significant toolkits are readily available for researchers with extensive technological skills; such toolkits can be applied to education and EdTech research, but they are not easy to use.

2.3.2. What about licensing or cost barriers?

Open-source tools without subscription costs are available, but they have limited capabilities. The most advanced open-source tool is ↑ASReview. Most commercial tools have a moderate associated cost, typically per month, per user (e.g., GBP 15/month/user). Figure 4.1. in Section 4.2. identifies the cost of web-based tools associated with each step of the literature review process.

2.3.3. How appropriate are the tools that are currently available? How advanced are they?

A variety of tools, with different degrees of appropriateness and levels of advancement, are available. Currently, no tool can fully automate the literature review process. However, many advanced and effective tools can support specific steps within a literature review (see Section 5 on integrated literature review tools). For example, ↑EPPI-Reviewer has an established track record and is widely used for some world-leading syntheses produced across diverse research fields.

A challenge with web-based tools is the need to check the input literature on which they operate. Semantic Scholar is one of the databases that has been available for some time and is widely used. However, it does not index education research publications extensively. Moreover, the precise AI processes used by web-based tools are typically not open to inspection. Such tools are only useful for gathering quick impressions. They would only be one component of more rigorous work: both AI-based and non-AI-based processes need to be transparent and 'explainable' (in the sense of 'explainable AI').

The question 'How appropriate are these existing tools?' is answered more comprehensively in Section 5. We discuss integrated literature review tools, such as fully integrated tools (5.1.), semi-integrated tools (5.2.), those that focus on literature search and discovery (5.3.), literature screening and categorisation (5.4.), and summarisation and writing assistance (5.5.). In addition, general purpose Large Language Models (5.6.), GPT (Generative

Pre-trained Transformer) Researcher (5.7.), and other tools (5.8.) are explored.

Regarding the question, 'How advanced are these AI tools?', Section 6 indicates how appropriate and effective various tools are in the areas of problem formulation (6.1.), literature searches (6.2.), screening for inclusion (6.3.), quality assessment (6.4.), data extraction (6.5.), and data analysis and interpretation (6.6.). See Figure 4.1. for an overview of different AI tools appropriate to the various steps of a literature review.

2.3.4. What tools are other organisations using to quickly and efficiently present a synthesis of the best evidence?

The answer to this question depends on the perspective. As noted in the previous sections, there are currently no tools that are (1) very easy to use (e.g., a web-based interface in the style of Google Scholar) or (2) that operate on the right input data and which would, therefore, reliably automate the literature review process fully. However, the ↑EPPI-Reviewer ecosystem and tools like it offer a platform that can significantly accelerate evidence synthesis.

2.3.5. Is there value in building a bespoke AI tool for 'education in LMICs' to help identify, review, and synthesise evidence for literature reviews?

There are several different answers to this question.

1. *Should EdTech Hub* ***experiment with AI tools*** *to help identify, review, and synthesise evidence for literature reviews?* In our view, the answer to this is yes. The potential payoff is very high and offers a significant first-mover advantage at this time.

2. *Would it be appropriate for EdTech Hub* ***to independently build a bespoke AI tool*** *for education in LMICs to help identify, review, and synthesise evidence for literature reviews?* If this were to be a comprehensive, easy-to-use tool, the effort for this — if carried by EdTech Hub alone — is unlikely to be justified (or indeed maintainable) beyond the life of the Hub. It should also be noted that, given recent advances (↑EPPI-Reviewer, ↑OpenAlex, ↑ASReview), the challenge would not necessarily be the development of new tools but rather the input data (i.e., the literature collection) curated for use by the AI tools.

3. *Should EdTech Hub* ***collaborate with others to explore building a bespoke AI tool*** *for education in LMICs to help identify, review, and*

synthesise evidence for literature reviews? Several organisations are interested in organising and synthesising evidence. EdTech Hub could play an important role in stimulating the sector to advance the use of AI for education in LMICs (including bespoke tools). Such an effort would necessarily involve building comprehensive databases, and encouraging others to register their research (typically in Crossref).

2.3.6. What are the pros and cons of building a bespoke AI tool focusing on education in LMICs, versus using an existing commercial product? What are the cost implications of the two options?

As noted above, a significant issue is the absence of a comprehensive database and existing commercial products that deliver on literature reviews for education/EdTech in LMICs.

EdTech Hub has already done some work on using AI tools for literature reviews (↑Haßler et al., 2021k). Some of these approaches were reused in a programme outside EdTech Hub, namely the England-focused collaboration between Open Development & Education and the Education Endowment Foundation (EEF) in a literature review focused on EdTech for disadvantaged children (↑Haßler et al., 2024).

Two activities would be conducive to exploring this question further and answering it more coherently, while also considering our prior work in this area:

1. **Convene stakeholders**: A moderate amount of funding could be utilised to explore AI collaboratively with a network of multiple stakeholders to coordinate and synthesise efforts, maximise outcomes, and determine how costs could be shared. (Perhaps 20% full-time equivalent (FTE) over one year, plus some moderate travel expenses).
2. **Undertake in-depth exploration of AI tools**: A moderate amount of funding could enable an in-depth exploration, which would involve several trials of software-developer-level AI tools, to illustrate the potential impact and determine costs.

   This exploration could include an extensive trialling of ↑EPPI-Reviewer and ↑ASReview, including some workshops for researchers from LMICs, to explore barriers to using these tools.

In addition, we propose conducting a coverage assessment of the ↑OpenAlex dataset. ↑OpenAlex already categorises publications according to Sustainable Development Goals (SDGs) (↑UN, no date). This existing categorisation could be further extended and tailored to the needs of education / EdTech within LMICs, including uses in 'living reviews'.

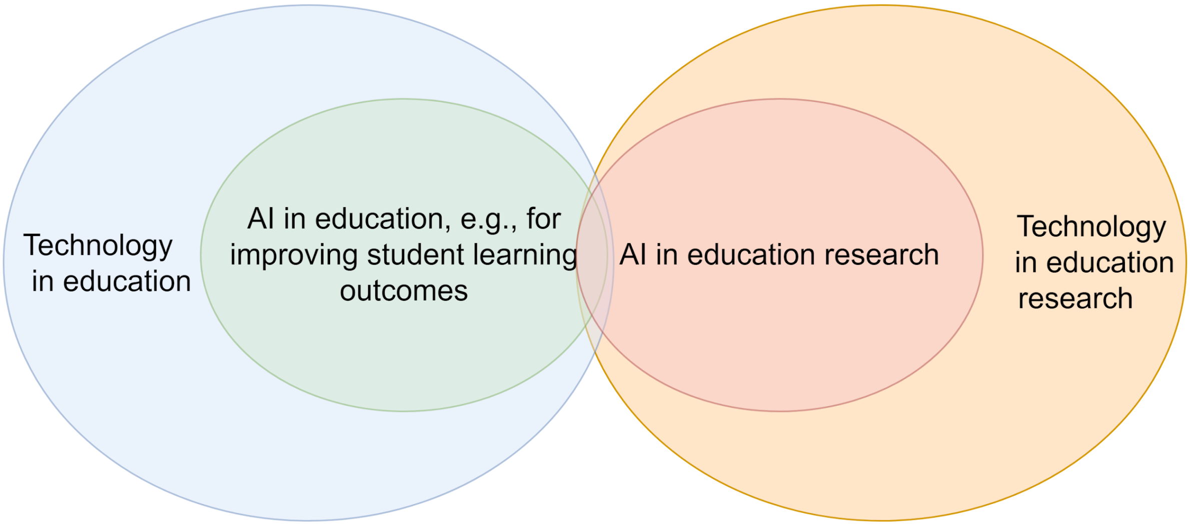
The activities mentioned above would allow informed, evidence-based pathways to be formed, working towards better use of AI tools to help identify, review, and synthesise evidence for literature reviews for education / EdTech in LMICs.

These activities are discussed in more detail in Section 7 as part of two overall recommendations (see Sections 7.1. and 7.2.)

3. AI and literature reviews

AI is beginning to transform many aspects of society, including the use of AI in education, for example, with a focus on improving learning outcomes. Figure 3.1. presents a visual representation of the use of technology for education (and AI within this), as well as the use of technology in research (and the use of AI within this). While the public interest in AI and the use of AI in education has been very visible, the use of AI in education research has been less so.

Figure 3.1. *Separating technology use for education from technology use for education research*



However, AI is also impacting traditional research practices in many areas. The potential of AI to augment and partially automate research has sparked vivid debates in many scientific disciplines, including the health sciences (↑Adams et al., 2013; ↑Tsafnat et al., 2014), biology (↑King et al., 2009), and management (↑Johnson et al., 2019).

Literature reviews are no exception to this: literature reviews draw on large and rapidly growing volumes of documents, i.e., partially structured (meta)data. Perhaps the use of AI for literature reviews has been less visible because methodological research on literature reviews could be considered a niche area. However, in a field like educational technology research, one would expect technology use for research to be much more prevalent than it is currently.

In contrast, within education research, natural science disciplines have utilised preprint servers for over 30 years (e.g., arXiv was founded in 1991), and these preprint servers are used very widely. However, such practices are less common in education research. Specifically on the absence of using AI techniques for literature reviews in education research, we note, for example, that the review article 'Automation of systematic literature reviews: A systematic literature review' (↑van Dinter et al., 2021) provides no examples from the field of education; likewise, a review of 50 years of conceptual modelling by ↑Storey et al. (2023) provides no reference to the fields of education or social sciences.

However, there is clearly significant potential for using AI in education and EdTech literature reviews. Similarly to ↑Wagner et al. (2022), writing in the field of information sciences, we believe that advancing knowledge in this area is promising because:

- rigorous standalone review projects require substantial efforts over a period of months;
- the volume of reviews published in education journals has been rising steadily, supplemented by a large and quickly growing body of grey literature;
- literature reviews involve tasks that fall somewhere on a spectrum between the mechanical and the creative.

Currently, the process of reviewing literature is mostly undertaken manually; while sample sizes are increasing — making more publications available — the increased sample sizes stretch resources and cognitive limits. The lack of comprehensive literature databases exacerbates the issue in education research, making processes even more onerous. Consequently, many review articles, problematically, do not have comprehensive coverage, often restricting their scope to a few top journals or search engines (↑Haßler et al., 2021k; ↑Xiao & Watson, 2017).

Although we are particularly interested in tools powered by 'advanced AI' (such as Large Language Models), we also consider more established users of AI, such as topic modelling.

4. Approach for this topic brief

The literature review process involves both creative and mechanical tasks; this creates viable opportunities for advanced AI-based tools to reduce the level of effort needed by prospective authors for time-consuming and repetitive tasks, leaving them free to dedicate more time to creative tasks that require human interpretation, intuition, and expertise (↑Tsafnat et al., 2014).

↑Saeidmehr et al. (2023) note that published research is seeing exponential growth, resulting in:

> *"a doubling of the scientific corpus for many fields every nine years, a trend that reflects the steady increase in the number of researchers and can be readily confirmed as having continued or even accelerated."* (↑Saeidmehr et al., 2023, p. 1)

While new AI tools and platforms are emerging rapidly, ↑Teijema et al. (2023) note the

> *"disparity between the rapid development of these methodologies and their rigorous evaluation."* (↑Teijema et al., 2023, p. 3)

4.1. Methodology for this topic brief

Our review borrows from the highly relevant review by ↑Wagner et al. (2022), who in turn collected evidence by surveying previous literature reviews of AI-based tools (e.g., ↑Al-Zubidy et al. 2017; ↑Harrison et al., 2020; ↑Jonnalagadda et al., 2015; ↑Kohl et al., 2018; ↑Marshall & Wallace, 2019; ↑Tsafnat et al., 2014; ↑van Dinter et al. 2021) and online registries (i.e., Systematic Review Toolbox).[1] We complemented this evidence by additional searches (with Google Scholar), reviewing papers that cited ↑Wagner et al. (2022), reviewing selected references, new review articles (policy analysis: ↑Lemire et al., 2023; bibliometrics: ↑Rowe et al., 2023; ↑Sarin et al., 2023; ↑Smith, 2023), as well as further online databases (↑van de Schoot, 2023; ↑Future Tools — Find The Exact AI Tool For Your Needs) and library guides (↑Xiao, no date).

We also reviewed prior EdTech Hub outputs pertaining to evidence review and synthesis, specifically:

[1] See http://systematicreviewtools.com. Retrieved 29 August 2024.

- Methodology for literature reviews ↑ (↑Haßler et al., 2021k, based on ↑Haßler et al. 2019h).
- Literature Reviews of Educational Technology Research in Low- and Middle-Income Countries: An audit of the field (↑Haßler et al. 2019g, and associated blog post: ↑Jordan, 2019).
- A scoping review of technology in education in LMICs—descriptive statistics and sample search results (↑Haßler et al. 2020v).

In addition to the literature research, we also corresponded with selected researchers in this field, who provided additional inputs.

The review of these sources surfaces several tools, including tools reviewed by ↑Wagner et al. (2022), and new tools; these tools were examined and tested if relevant to the topic of this review.

4.2. Results

An overview of the new tools discovered and considered relevant to this topic brief, is available in Figure 4.1. below.

Some tools support multiple steps of the review process (e.g., ↑EPPI-Reviewer). These tools tend to focus on data, workflow, and collaboration management functionality without necessarily drawing on AI capabilities. This commentary focuses on tools supporting individual steps because they tend to be more amenable to code inspection and extension (i.e., published under open-source, non-commercial licences) and independent validation. These tools are described in Section 5.

Tools specific to individual stages of the literature review process are detailed in Section 6, which discusses the steps of the literature review process, outlining relevant AI-based tools that could be used at each step.

Figure 4.1. *AI-based tools for the different steps of the literature review process in education research.*

	AI-based tools	**Cost**	**Potential for AI-support**
Step 1. Problem formulation	Programming libraries supporting thematic analyses based on Latent Dirichlet Allocation models (example paper: ↑Antons & Breidbach, 2017; example from education research: ↑Bhutoria, 2022).	N/A	Moderate potential with AI potentially pointing researchers to promising areas and questions or verifying research gaps.
	Graphical User Interface (GUI) applications and programming libraries supporting scientometric analyses (↑Swanson & Smalheiser, 1997).	N/A	
	Web-based tools: ↑Elicit	Free Trial (free 5,000 credits), Pay-as-You-Go (USD 1/1,000 credits) and Enterprise Plan (Custom pricing)	

	AI-based tools	Cost	Potential for AI-support
Step 2. Literature search	TheoryOn (↑Li et al., 2020) enables ontology-based searches for constructs and construct relationships in behavioural theories	N/A	Very high potential since the most important search methods consist of steps that are repetitive and time-consuming, that is, amenable to automation
	↑litbaskets (↑Boell & Wang, 2019) supports researchers in setting a manageable scope in terms of journals covered	The service is realised through Scopus, suggesting that users need access to Scopus to utilise the features.	
	↑LitSonar (↑Sturm & Sunyaev, 2019) offers syntactic translation of search queries for different databases; it also provides (journal) coverage reports	Currently provided only to members of cooperating institutions due to licensing restrictions	
	↑Elicit	See above	
	↑ORKG Ask	Free to use/open source	

Step 2. Literature search	↑EPPI-Reviewer is a web-based software designed to manage and analyse literature review data, including systematic reviews, meta-analyses, framework syntheses, and thematic syntheses. It is developed and maintained by the EPPI Centre at the UCL Institute of Education, University of London.	**User fee:** GBP 10 per month. This gives access to the software and the ability to create and maintain an unlimited number of non-shareable reviews. **Shareable review fee:** GBP 35 per month for each shareable review. All users in a shareable review must have active user accounts. **Site licence:** Available for organisations conducting multiple reviews with many users.	

	AI-based tools	Cost	Potential for AI-support
Step 3. Screening for inclusion	↑ASReview (↑van de Schoot et al., 2021) offers screening prioritisation	Free and open-source software	■ High potential for semi-automated support in the first screen, which requires many repetitive decisions ■ Moderate potential for the second screen, which requires considerable expert judgement (especially for borderline cases)
	Automated detection of implicit theory (ADIT) approach (↑Larsen et al., 2019) for researchers capable of designing and programming machine learning classifiers (research on the Technology Acceptance Model).		
	↑Rayyan	**Individual plans:** ■ **Free plan:** USD 0, free forever. ■ **Professional plan:** USD 8.25 per month, billed annually. ■ **Student plan:** USD 4 per month, billed annually. **Teams plans:** ■ **Pro team:** USD 8.25 per user, per month, billed annually. ■ **Teams+:** USD 24.99 per user, per month, billed annually. **Enterprise plans:** Custom pricing	

	AI-based tools	Cost	Potential for AI-support
Step 4. Quality assessment Meta-analysis, qualitative systematic reviews	Statistical software packages (e.g., ↑RevMan)	**For individuals:** **Standard rate:** GBP 100.00 + VAT (EU & UK). **Academic:** GBP 85.00 + VAT (EU & UK). **Student:** GBP 65.00 + VAT (EU & UK). **For organisations:** Custom pricing	Low to moderate potential for semi-automated quality assessment
	↑RobotReviewer (↑Marshall et al., 2015) for experimental research	Pricing information is not available. The source code is available on the website.	

	AI-based tools	**Potential for AI-support**
Step 5. Data extraction	Software for data extraction and qualitative content analysis (e.g., Nvivo and ATLAS.ti) offers AI-based functionality for qualitative coding, named entity recognition, and sentiment analysis	▪ Moderate potential for reviews requiring a formal data extraction (descriptive reviews, scoping reviews, meta-analyses and qualitative systematic reviews) ▪ High for objective and atomic data items (e.g., sample sizes); low for complex data which has ambiguities and lends itself to different interpretations (e.g., theoretical arguments and main conclusions)
	WebPlotDigitizer and Graph2Data for extracting data from statistical plots	
	↑Elicit	

	AI-based tools	**Potential for AI-support**
Step 6. Data analysis and interpretation	Descriptive synthesis: Tools for text-mining (↑Kobayashi et al., 2017), scientometric techniques, and topic models (↑Nakagawa et al., 2019; ↑Schmiedel et al., 2019), and computational reviews aimed at stimulating conceptual contributions (↑Antons et al., 2021).	■ Very high potential for descriptive syntheses ■ Moderate potential for (inductive) theory development and theory testing ■ Low, non-existent potential for reviews adopting traditional and interpretive approaches
	Theory building: Examples of inductive (computationally intensive) theory development (e.g., ↑Berente et al., 2019; ↑Lindberg, 2020; ↑Nelson, 2020).	
	Theory testing: Tools for meta-analyses (e.g., ↑RevMan and ↑dmetar)	

5. Integrated literature review tools

We note that several 'integrated' tools offer larger workflows, in some cases, the full literature review workflow. They offer multiple AI / tech tools in the literature review process, but no single tool can carry out a comprehensive review.

This section reviews **integrated** tools that cover multiple stages of the literature review workflow. Many of these tools are web-based. Section 6 below discusses tools that are specifically relevant at different stages of a literature review.

The present section makes the case that:

- With some notable exceptions, many integrated web-based tools have unknown or poor coverage, which is problematic.
- Such integrated web-based tools often do not state what precise workflows or algorithms are used, which is also problematic.
- However, such tools often have very attractive, easy-to-use interfaces, which is helpful, and allows them to compete with more established tools.

Below, we build on Figure 4.1., by identifying AI tools that support education-related literature reviews by being fully integrated (5.1.) or semi-integrated (5.2.). We discuss ↑EPPI-Reviewer (5.1.1.) and ↑ASReview (5.1.2.) in more detail while exploring additional tools that could potentially be used to assist with literature reviews; specifically, we review ↑DistillerSR (5.1.3.) and ↑Colandr (5.1.4.), and the semi-integrated tools, ↑Iris.ai (5.2.1.), ↑Lateral.io (5.2.2.), ↑SciSpace (5.2.3.), and ↑Scanlitt (5.2.4.), focusing on the extent of their functionality.

5.1. Fully integrated tools

This subsection presents fully integrated tools which offer support at all stages of the literature review process.

5.1.1. EPPI-Reviewer

↑EPPI-Reviewer is subscription and web-based software that assists with several types of literature reviews (meta-analyses, systematic reviews, narrative reviews, meta-ethnographies, and more). It is capable of managing and analysing both large- and small-scale data. ↑EPPI-Reviewer can automate several processes in literature reviews, including deduplication, clustering, and screening, and it contains five different study-type classifiers (randomised controlled trials, systematic reviews, economic evaluations, Covid-19 categories, and Long Covid categories). It also integrates with ↑RobotReviewer, a machine-learning system supporting evidence synthesis and classification. ↑EPPI-Reviewer can import and manage references and store PDF files. It has a coding function that allows users to include or exclude different parameters for a review. Using a complementary tool, ↑EPPI-Reviewer, users can also generate evidence gap maps based on a literature review conducted in ↑EPPI-Reviewer. The latest version (June 2020) is ↑EPPI-Reviewer 6, although it uses the same data from Version 4.

Overall, ↑EPPI-Reviewer works best as a tool for screening and extracting data for review. However, ↑EPPI-Reviewer can also assist with literature searches as it can be integrated with the ↑OpenAlex database. On its own, ↑EPPI-Reviewer cannot assist in an initial literature search and functions best when identified studies are imported into the software for screening and extraction. The use of EPPI Reviewer with a suitable automated literature search tool holds promise for improving the timeliness and efficiency of literature review workflows. The EPPI-Reviewer site lists AI-based automation tools (↑EPPI Reviewer, no date).

5.1.2. ASReview

↑ASReview (↑van de Schoot et al., 2021) offers a promising open-source option with its range of machine learning classifiers (including naive Bayes, support vector machines, logistic regression, and random forest classifiers). It learns from initial inclusion decisions and leverages these insights to present researchers with a prioritised list of papers (i.e., the titles and abstracts), proceeding from those most likely to be included to those least likely.

↑ASReview is open source, so it could potentially connect with the OpenAlex database. ↑ASReview uses active learning algorithms to reorder records based on their predicted relevance. This approach helps researchers find relevant records more quickly than traditional methods, potentially reducing screening time by up to 95% (↑van de Schoot et al., 2021). Users provide initial input by labelling at least one relevant and one irrelevant record. The software's AI model, Elas, then learns from these decisions to present the next most relevant record for screening. ↑ASReview doesn't generate results from specific databases. Instead, it allows users to import their datasets collected from various research databases like Web of Science, PubMed, etc. The software supports datasets in RIS, CSV, and Excel formats. ↑van de Schoot (2023) notes that ↑ASReview, developed at Utrecht

University, helps scholars and practitioners to get an overview of the most relevant records for their work as efficiently as possible while being transparent in the process. It allows multiple machine learning models and features with exploration and simulation modes, which is especially useful for comparing and designing algorithms. Furthermore, it is intended to be easily extensible, allowing third parties to add modules that enhance the pipeline with new models, data, and other extensions.

5.1.3. DistillerSR

↑DistillerSR is subscription, web-based systematic review software that uses AI and intelligent workflows to automate the management of every stage of a literature review: searching, screening, text retrieval, data extraction and appraisal, and reporting. All stages are configurable based on user needs.

With AI-driven duplicate detection, ↑DistillerSR is integrated with data providers to enable automated literature searches and importing references. AI is used to automate screening based on user preferences, and its developers claim it reduces screening time by up to 60%. AI is also used to identify conflicts and provide a quality check of screening.

The tool has existing content-provider integrations and ad-hoc document retrieval to assist with the collection and copyright management of full-text articles. Data extraction is supported by pre-built templates and configurable forms that support validations, calculations, and cleaning of complex datasets. The software includes a customisable reporting engine to generate and disseminate reports and updates and allows for integration with third-party reporting applications. It also provides an audit trail. In particular, the tool supports project management and provides real-time metrics to monitor teams and progress.

↑DistillerSR is a comprehensive and customisable tool and a very promising application of AI for the literature review process. However, the current iteration seems heavily focused on supporting medical studies, and many third-party integrations have a similar focus. As such, its suitability for literature reviews in different fields may not be as efficient. It is also important to note that many functions described here from ↑DistillerSR are divided into different modules (CuratorCR, LitConnect, AI Classifiers, Application Programming Interface (API) Integration). The provider does not necessarily sell these modules together; their inclusion depends on the subscription plan.

5.1.4. Colandr

↑Colandr (machine-learning assisted) is a free, web-based, open-access tool designed for conducting evidence synthesis projects, including systematic and scoping reviews. It supports various stages of the systematic review process, including protocol development, citation deduplication, article screening, data extraction and coding, and manuscript development. The tool employs machine learning to facilitate evidence synthesis, optimising the process of citation sorting by relevance and semi-automating the classification of included documents.

Colandr can be used collaboratively with teams of any size, supporting cooperative work and cross-checking between team members. It allows users to upload PDFs and extract data from full texts using natural language processing. Extracted data and screening decisions can be exported in CSV format (see Colandr for Systematic Reviews [↑Kahili-Heede, no date]).

5.2. Semi-integrated tools

Several tools do not support the entire literature review process in the same way as the above tools do (5.1.); however, they still offer a somewhat integrated environment or can be integrated with various other software environments, which is why we refer to these tools as 'semi-integrated'.

5.2.1. Iris.ai

↑Iris.ai is a forthcoming subscription service that provides an AI-driven 'Researcher Workspace' tool suite to assist with research and systematic reviews. The platform holds value in using AI to support several steps in the literature review process, including initial search, screening, data extraction, and analysis.

The tool suite includes different modules that assist and help automate content-based searches, context and data filtering, data extraction and systematisation, and the analysis of document sets. It can also provide automated summaries of included papers and allows users to distil insights through a chat feature, enabling interactions between researchers and data insights. It claims the Researcher Workspace can save up to 75% of manual effort in the research process.

However, the tool currently appears to be focused on industry- and science-related research topics. It is unclear what integrations the platform supports and the extent to which it accesses education research. The website does not offer a standardised subscription model.

5.2.2. Lateral

↑Lateral.io is a subscription service that focuses on using AI-powered tools to assist with the organisation and process of literature search, screening, and data extraction. It offers users a paper search integrated with different third-party applications, such as Semantic Scholar, to search for relevant literature. It also has several AI-powered tools, such as concept recognition, a smart PDF reader, and a search function to help automate literature screening data extraction.

↑Lateral.io is a promising tool that can enable the automation of the early stages of a literature review to help streamline workflows. However, it is unclear how robust the literature search function is for education research.

5.2.3. SciSpace

↑SciSpace, formerly known as Typeset, is a platform designed to streamline the research workflow. SciSpace facilitates the discovery, creation, and publication of research papers. It offers tools for understanding academic texts in simpler language and finding connected papers, authors, and topics. It is an AI-powered tool that aids in comprehending and elaborating academic texts. SciSpace is best suited for researchers, academic professionals, and students involved in writing, collaborating, and publishing research papers. SciSpace has a forever free plan with limited feature access. SciSpace Premium is available for USD 12 per month, billed annually, and custom pricing is available for teams and enterprises.

5.2.4. Scanlitt

↑Scanlitt is a digital research assistant platform designed to streamline literature review and knowledge acquisition for the scientific community with the following core features:

- **ARTIREV:** This feature of Scanlitt helps in identifying relevant scientific articles, clustering them for better understanding, and prioritising readings. It caters to different use cases, such as for academics, students, medical practitioners, and institutions, providing tailored solutions for each. ARTIREV's process involves downloading, cleaning, analysing data, and interpreting the results. This process is presented through a dynamic interface with radial dendrograms for quick identification of article groups, accompanied by word clouds and additional information for each article.

- **DATAMAN:** A bibliographic database specifically for management science. It indexes journals in the management field and is used for tracking publications, authors, institutions, or thematic searches using keywords.

Pricing and subscription options:

- **Offline and in-depth exploration of literature:** Offers offline use, comprehensive analysis without article limits, compatibility with various databases, and availability for individual or landline subscriptions.
- **Online and in-depth exploration of a scientific object:** This option is available online, supports multiple devices, provides complete analysis limited to 500 articles, and is compatible with various databases. It offers both individual and institutional subscriptions.
- **Access to relevant knowledge with a click:** Scanlitt is compatible with multiple devices, providing simplified results limited to 120 articles, and is compatible with DATAMAN data via API.
- Scanlitt offers a free trial of Artirev, allowing potential users to explore its functionalities before subscribing. However, during our exploration of the platform, we noted that support videos are in French.

5.3. Focus on literature search and discovery

5.3.1. Semantic Scholar

Semantic Scholar is a free academic search engine that uses machine learning to provide brief summaries of literature. Users can apply key topics or concepts to search from over 214 million papers to identify appropriate papers to include in a literature review. It can provide short summaries of papers to help identify potentially relevant papers; it also provides organisational features such as an online library, which works with an AI-powered research feed to enable literature recommendations. Other tools include citation analysis and entity recognition, and they also provide information on the open-access status of papers.

Semantic Reader is an emerging application that aids reading of academic literature through AI to support comprehension. At the time of writing, it is only available for most arXiv papers on Semantic Scholar. Features are growing, and it can currently provide citation cards that include summaries, tables of content, and online library integration.

Fundamentally, Semantic Scholar is a research search engine that uses AI-powered tools to help with literature searches and citations. It can be a valuable tool to integrate into the early-stage workflow of the literature review process. That said, it currently focuses on scientific papers, and the search function is not as robust for education research.

5.3.2. Research Rabbit

↑Research Rabbit is a free, AI-powered tool that assists with searching, organising, and curating literature. Its unique function provides visualisations of 'paper networks' based on the topics or papers the researcher inputs into the search engine. These visual networks can be used to explore and/or curate literature. It also functions as a collaborative workspace; multiple users can access and comment on different reviews and visualisations. It can also provide personalised recommendations and is integrated with Zotero for citation purposes.

5.3.3. Consensus

↑Consensus is a search engine in its beta phase that uses language models to identify and synthesise insights from academic research papers. Consensus' source material comes from the Semantic Scholar database. The main purpose of ↑Consensus is to provide a list of up to 20 of the most relevant papers related to a research question or phrase, input into the engine. The language model then ranks the search results by relevance to the query.

↑Consensus' value lies somewhere between literature search and early data extraction. While it cannot be used to search a high volume of papers, it can help produce general insights from the most relevant literature on a topic. Used in conjunction with other tools, it can improve the early workflow of a literature review process. Its use of the Semantic Scholar database might limit its applicability to education research.

5.4. Focus on literature screening and categorisation

5.4.1. Covidence

↑Covidence is a tiered subscription, web-based tool that assists with systematic reviews. It is aimed at supporting institutions and organisations, such as universities, government organisations, and research institutes. As such, ↑Covidence enables small and large teams to use it to collaborate on the review process. ↑Covidence works with reference management software such as Zotero to import citations for review.

Covidence is better described as an assistive and user-friendly tool that aids in literature review screening, deduplication, and risk-of-bias assessment.

5.4.2. Abstrackr

↑Abstrackr is developed and maintained by the Center for Evidence Synthesis in Health at Brown University. It is a free, open-source, web-based application aimed at optimising the citation screening step for systematic reviews. The tool includes a web-based annotation feature, allowing review participants to screen citations for relevance collaboratively. It employs machine learning technologies to semi-automate the citation screening process, which is still in development. The software allows for importing citations from databases like RefMan or PubMed. It provides functionality for single or double-screening citations and a decision reconciliation mode for reviewing citations with unclear relevance.

↑Abstrackr is best suited for researchers, academics, and professionals involved in conducting systematic reviews, particularly in the biomedical field. It is designed to aid these users in managing the growing volume of biomedical literature and make systematic reviews less onerous. Abstrackr is a free tool, making it accessible to a wide range of users without budget constraints.

5.4.3. RobotAnalyst

↑RobotAnalyst (National Centre for Text Mining) is a web-based software tool developed to assist in the literature screening phase of systematic reviews. It combines text-mining and machine learning algorithms to organise references by content and prioritise them based on a relevancy classification model that is trained and updated throughout the process. This tool is particularly useful for researchers and professionals engaged in systematic reviews, helping them to manage and prioritise a large volume of literature efficiently. According to ↑van de Schoot (2023),

> *"RobotAnalyst was developed as part of the Supporting Evidence-based Public Health Interventions using Text Mining project to support the literature screening phase of systematic reviews."*

RobotAnalyst is free to use.

5.4.4. SWIFT-Active Screener

↑SWIFT is an acronym for Sciome Workbench for Interactive Computer-Facilitated Text-mining. SWIFT-Active Screener is a web-based, collaborative software application specifically designed for systematic reviews. It aims to reduce the time and effort required in the literature screening phase of systematic reviews. It employs statistical and computational methods to prioritise articles for inclusion in systematic reviews. Moreover, it includes an algorithm to estimate recall while users work, providing a statistical basis for deciding when to stop screening. The application significantly reduces the screening burden compared to traditional methods, achieving high recall rates with fewer articles screened. For example, in tests on diverse systematic reviews, it resulted in an average 54% reduction in screening burden while maintaining 95% recall or higher. The tool is designed to be easy to use, with a simple yet powerful graphical user interface, and offers rich project status updates. SWIFT-Active Screener is best suited for researchers, academics, and professionals conducting systematic reviews, particularly in areas like government, industry, and non-profit research organisations. It is free for the public to use.

5.5. Focus on summarisation and writing assistance

5.5.1. SciPub+

↑SciPub+ is a recent subscription-based tool that features a collection of ten AI assistants designed to support the whole workflow of academic writing. The AI assistants guide individuals through key parts of the academic writing process, of which literature reviews are one component. The literature review AI assistant, like the others, makes use of a form that asks the researcher important questions related to their project to enable the AI assistant to generate a draft literature review.

↑SciPub+ is valuable in automating the drafting of a written literature review, although it is limited in assisting in the larger process of literature reviews as it is a writing-focused tool. As such, it cannot assist in actual literature searches, filtering, or data extraction. It may have value in the later stages of a literature review once a draft is ready to be written.

5.5.2. Paperdigest

↑Paperdigest is an AI-powered tool designed to summarise academic articles, providing a quick and efficient way for researchers, students, and science communicators to grasp the core ideas of a paper. It uses advanced algorithms to generate concise summaries of research papers, effectively capturing the key points and main subjects. Users can quickly summarise a research paper by entering its DOI or PDF link on the PaperDigest website. It highlights specific values, results, comparisons, and other crucial information from the paper, facilitating a deeper understanding of the research. Registered users can upload PDFs directly from their computers for summarisation.

PaperDigest works primarily with open-access articles, meaning it summarises freely available content not behind paywalls. The specific databases it draws from are not explicitly mentioned, but it likely includes major academic databases and journals that offer open-access content. PaperDigest is a free tool. There are no charges for using its basic features, including the summarisation of articles using DOI or PDF links.

5.5.3. Scholarcy

↑Scholarcy is an AI-powered tool designed to assist academic research by quickly analysing and summarising research articles, reports, and book chapters. It summarises entire papers, including references, and rewrites statements in the third person for easy citation. It also highlights key claims, statistics, terms, and abbreviations. The tool links to open-access versions of each cited source, reducing the need for manual searching. It also extracts figures and tables from papers, providing them in a format suitable for further analysis.

↑Scholarcy offers browser extensions for Chrome, Firefox, and Edge, and integrates with the Scholarcy Library for storing and organising summary cards. Scholarcy does not specify the research databases it uses to generate results. However, it finds references by locating open-access PDFs from sources like Google Scholar and arXiv and uses the Unpaywall API to assist with this.

Scholarcy offers both free and paid-for plans. The free plan includes browser extensions and flashcards, while the paid-for plans offer additional features like a personal library for summary flashcards and academic institution licences. The personal library plan starts at USD 4.9 per month, and the academic institution licence starts from USD 8K+ per year (see ↑Viraj, no date for a review of Scholarcy pricing and features).

5.5.4. Elicit

↑Elicit is an AI research assistant designed to help researchers automate time-consuming tasks such as summarising papers, extracting data, and synthesising findings. Users can search for research papers using natural language queries, get one-sentence abstracts, select relevant papers, and extract details into organised tables. Elicit also identifies themes and concepts across multiple papers, enhancing the literature review process. With a database of 125 million academic papers, Elicit saves researchers time and effort, making it easier to stay well-informed and conduct systematic reviews.

In our exploratory trialling of ↑Elicit, researching an education topic on disadvantaged children, elicit.org only found 5% of the 250 studies included in the final review. While the features of elicit.org are compelling, this lack of results is not surprising as elicit.org is based on the Semantic Scholar database, which has poor coverage of education journals.

5.5.5. ORKG ASK

↑ORKG Ask is an advanced open-search system designed to help researchers, academics, and enthusiasts find and extract valuable information from a vast corpus of research articles. Similar to ↑Elicit, users can simply ask a question in natural language. ORKG Ask will handle the rest by understanding the context of the query to find semantically similar research articles through its semantic search feature. It conducts global searches across the entire indexed corpus (76m articles) for comprehensive results and allows users to refine their search results with metadata filters. Additionally, ORKG Ask can extract specific properties or information from related research papers for detailed insights. The system employs a sophisticated pipeline that starts with query submission, followed by a semantic search using an embedding model to encode queries and search for semantically similar articles using an 'Approximate Nearest Neighbour' algorithm. Once relevant articles have been identified, a Large Language Model extracts the necessary information, and users can enhance their search with metadata filters for more precise results. Technically, ORKG Ask uses ↑Qdrant for storing and retrieving vector representations of research articles efficiently, the ↑Nomic embedding model to encode search queries and research articles into high-dimensional vectors for semantic search, and the ↑Mistral Instruct 7B v0.2 LLM to extract and interpret relevant information from the selected research articles. The research articles are sourced from the ↑CORE dataset, a comprehensive collection of open-access research literature.

The service offers a 'my library' service, where users can upload their own datasets.

5.6. General Purpose Large Language Models

ChatGPT, developed by OpenAI, is a highly advanced Large Language Model that has significantly impacted various fields, including research. In our view, ChatGPT (4.o/o1/o1-mini) levels of responses can be considered comparable to final-year undergraduate / first-year graduate levels. At these levels, knowledge and insights are well documented in books. By contrast, rigorous research synthesis requires access to journals.

For example, in our experience, ChatGPT can produce interesting research designs in response to research questions. Similarly, our experience shows that ChatGPT can also answer questions about short text pieces (see ↑Haßler et al., 2024).

However, research synthesis as such is not really possible with ChatGPT (see Figure 5.1. for a typical ChatGPT 4o response). While it is possible to make questions more specific, the pattern of responses is similar: relevant websites are found, and results are presented. While this is undoubtedly useful, particularly for graduates or new researchers entering new areas of research, it does not constitute rigorous synthesis. Similarly, so-called 'custom GPT models' tailored to specific research domains or datasets can enhance the relevance and accuracy of the information generated for literature reviews.

Figure 5.1. *ChatGPT 4o response: What research evidence is there about teacher allocation in low-income countries?*

Research on teacher allocation in low-income countries highlights several key issues and strategies.

- **Challenges in Recruitment and Retention**: Recruiting and retaining teachers in hard-to-staff schools, particularly in rural and impoverished areas, is a significant challenge. Studies show that financial incentives, such as higher salaries, hardship allowances, and housing benefits, can effectively attract teachers to these regions and reduce turnover. However, non-financial incentives, such as professional development opportunities and improved working conditions, also play a crucial role (Teacher Task Force) (Open Book Publishers).

  Equity in Teacher Distribution: Ensuring equitable distribution of teachers is critical to addressing educational disparities. Many countries use teacher allocation formulas based on student-to-teacher ratios, but these often fail to consider the varied needs of different regions. Innovative approaches, like using Geographic Information Systems (GIS) for mapping and deploying teachers, have shown promise in improving equity by more accurately matching teacher supply with demand across different areas (Teacher Task Force) (IIEP Policy Toolbox).

  Integrated Information Systems: The development of integrated teacher information systems (e.g., T-EMIS) can significantly enhance the efficiency and transparency of teacher deployment. These systems help manage teacher data comprehensively, reducing political and social biases in the allocation process and ensuring that deployment decisions are based on clear, pre-set criteria such as seniority and merit (IIEP Policy Toolbox).
- **Impact of Teacher Quality**: Research consistently shows that teacher quality is a major determinant of student outcomes. Efforts to improve teacher quality in low-income countries include providing ongoing professional development, implementing rigorous teacher training programs, and setting high standards for teacher certification. However, maintaining and improving teacher quality remains a complex challenge, particularly in contexts with limited resources (Open Book Publishers).
- **Policy Implications**: Effective policies for teacher allocation in low-income countries often involve a combination of strategies tailored to local contexts. This includes financial and non-financial incentives, the use of technology for efficient management, and continuous support for teacher professional development. Policymakers are encouraged to involve all stakeholders, including teachers and teacher unions, in the decision-making process to ensure the sustainability and acceptance of these policies (IIEP Policy Toolbox).

In summary, addressing the challenges of teacher allocation in low-income countries requires a multifaceted approach that combines equitable resource distribution, effective use of technology, and policies that support both recruitment and retention of high-quality teachers.

5.7. GPT Researcher

As a recent article explored, Large Language Models assist in writing Wikipedia-like articles (↑Shao et al., 2024). Inspired by this, the ↑GPT Researcher tool showcases how a team of AI agents can work together to research a given topic, from planning and writing to publication. GPT Researcher is an open-source autonomous agent designed for thorough online research, producing detailed, factual, and unbiased reports with customisable options. Inspired by recent AI advancements, it offers improved speed and reliability through parallelised agent work. Its mission is to provide accurate information by leveraging AI, overcoming the limitations of current Large Language Models, which often rely on outdated data, risk hallucinations, and produce short, biased outputs. GPT Researcher addresses these issues using a broader range of sources for more objective research conclusions.

5.8. Other tools

In this subsection, we note other tools that we found but could not or decided not to review. ↑Parsifal focuses specifically on literature reviews in software engineering. Two tools had limited availability (↑srdb.pro; ↑SESRA). ↑Feynman AI has been advertised but appears not to have entered production. We also note ↑Grantable, which supports the writing of grant applications.

Perhaps on a tangent, ↑Perplexity is a conversational search engine designed to provide accurate and contextual answers to complex queries. It can search the internet, including domains like Wolfram|Alpha, Wikipedia, Reddit, YouTube, News articles, and Academic Papers. Users can save search threads, share them, and interact with threads shared by others. Account holders can curate the sources Perplexity AI uses for their searches, ensuring relevance and accuracy. Powered by GPT-4, the Copilot feature helps guide users' search experiences by asking clarifying questions and refining the search process. It also offers a Chrome extension, allowing users to use the tool anywhere on the internet, including page- and domain-specific answers and article summaries. Perplexity AI offers both free and paid-for versions. The free version includes basic features, while the premium plan, priced at USD 20 per month or USD 200 per year, provides unlimited copilot usage and access to advanced language models like GPT-4 (↑Aayush, 2023).

6. Tool reviews

As noted above, the subsections below follow the steps of the literature review process, outlining relevant AI-based tools specific to various stages of the process. For web-based, integrated tools, see Section 5. The subsections correspond with entries in the tables in Figure 4.1.

6.1. Problem formulation

At present, there is only moderate potential for using AI to support problem formulation or verify research gaps. Tools such as ↑Elicit and ↑Consensus, which have multiple functions but are also helpful in quickly testing different research questions, are emerging.

6.2. Literature searches

We agree with ↑Wagner et al.'s (2022) assessment that the area of literature searches has a very high potential for using AI. We note that the AI approach used by prior EdTech Hub work, which uses Natural Language Processing, falls into two domains: literature searches and screening (↑Haßler et al., 2021k).

For comprehensive reviews, automated, cross-database searches should be considered the best research practice for systematic literature reviews in the fields of education and EdTech. The need for comprehensive, cross-database searches is motivated by the observation that "no database contains the complete set of published materials" (↑Xiao & Watson, 2017: p. 11); while this assertion dates back to 2017, it still holds today. Our previous work (↑Haßler et al., 2020) suggests that, unlike health databases, education publication databases only overlap by 30%–50%, which makes structured approaches across multiple databases necessary, as well as the need to apply multiple search techniques (↑Papaioannou et al., 2010; ↑Templier & Paré, 2018). Our cross-database tools (↑Haßler et al., 2020) predate ↑LitSonar but have similar components; our tools (↑Haßler et al., 2021k) also offer a software development kit, enabling large-scale retrievals from commonly used portals (Scopus, Web of Science, ProQuest, CrossRef, Directory of Open Access Journals (DOAJ), etc.).

Limited interoperability (accessibility via APIs) is still a major obstacle to breaking the data processing pipeline between the database and local repositories of research teams, introducing manual database queries, and duplicate checking as potential sources of errors. Ultimately, automated searches also further the goal of transparent reporting (information science: ↑Templier & Paré, 2018), as well as repeatability and reproducibility (information science: ↑Cram et al., 2020).

↑Wagner et al. (2022) note that a prevalent challenge for literature reviews in the social sciences is the lack of databases comprehensively curating research published in the main outlets, including journals and conferences (↑Brocke et al., 2015). Within the domain of EdTech, EdTech Hub's evidence library is one such effort to comprehensively curate new research on EdTech in low-income countries (↑Haßler et al., 2024).

One use of AI for literature searches includes deduplication to manage the outputs of automated searches. Automated searches surface large numbers of publications that include many duplications. Natural Language Processing can support the removal of duplications. AI can also support the process of backward and forward 'snowballing' (backward and forward citation searching). Currently, few literature databases include citation trees; the commercially available examples include Web of Science, ↑Scite, and Google Scholar. Figures 6.1., 6.2., and 6.3. below illustrate citation searching in the various tools (forward/backward snowballing). We note that the three tools provide different citation estimates (Web of Science: 170, ↑Scite: 180, Google Scholar 528). Web of Science (6.1.) also provides citations (forward/backward snowballing), while the other tools do not. ↑Scite (6.2.) not only provides citations but uses AI to attempt a critical appraisal of the citation: citations that 'support' the original claims, citations that only 'mention' the original claims, and citations that 'contrast' the original claims. Notably, Google Scholar (6.3.) is the only tool that allows for searching within citing papers.

Figure 6.1. *Citation and references for a publication in Web of Science — forward and backward snowballing.*

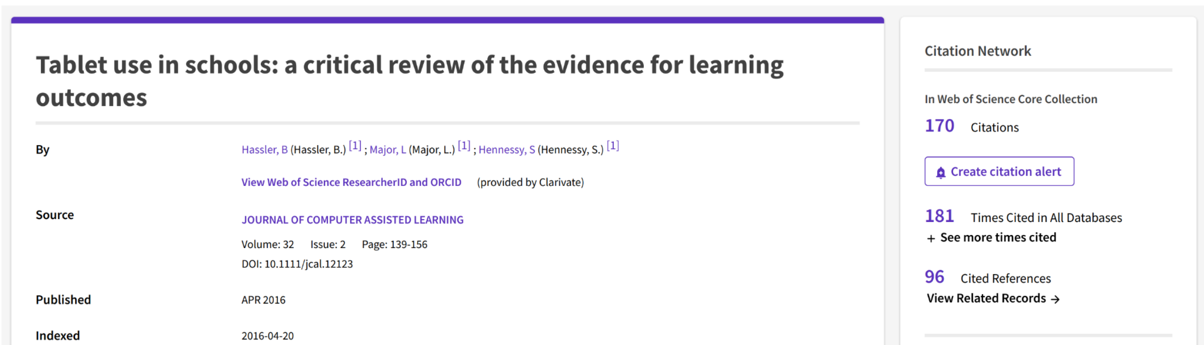


Figure 6.2. *The same article viewed on the Journal of Computer Assisted Learning (JCAL) website, with the ↑Scite plugin active—Scite provides forward snowballing only but indicates supporting/mentioning/contrasting with a total of 186 citing articles*

Figure 6.3. *The same article viewed on Google Scholar, indicating 528 citing articles and illustrating the ability to search within citing articles*

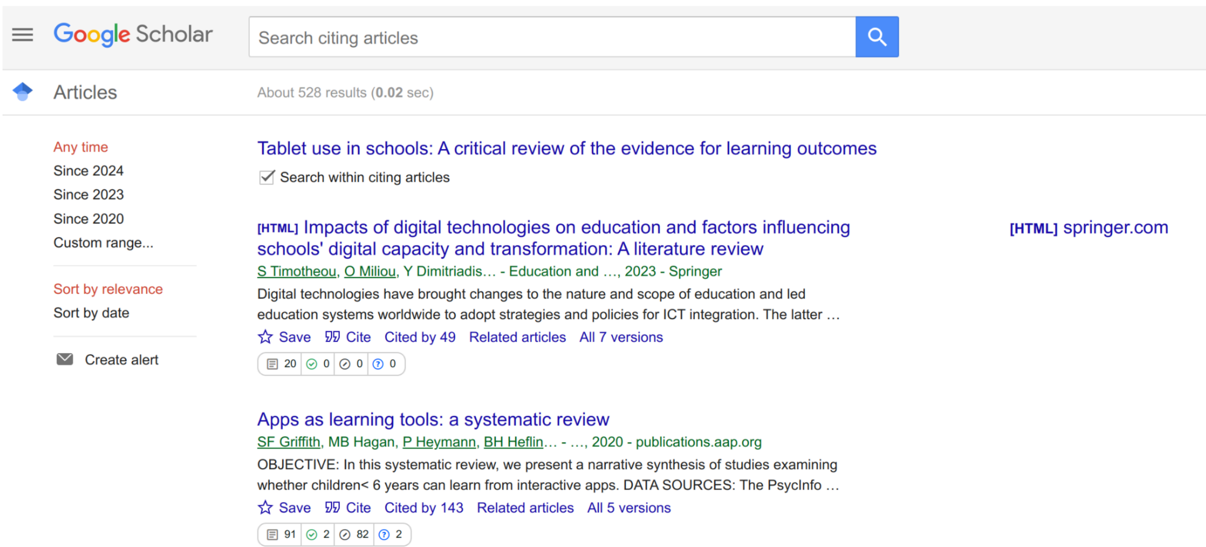


Figure 6.4. *The same article viewed on Open Development & Education's evidence library together with citations and citing articles (forward/backward snowballing; URL:* https://docs.opendeved.net/lib/9IYKEUKJ).

Open Development & Education / Evidence Library / Tablet use in schools: a critical review of...

TABLET USE IN SCHOOLS: A CRITICAL REVIEW OF THE EVIDENCE FOR LEARNING OUTCOMES

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Resource type Journal Article

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Title Tablet use in schools: a critical review of the evidence for learning outcomes

Abstract The increased popularity of tablets in general has led to uptake in education. We critically review the literature reporting use of tablets by primary and secondary school children across the curriculum, with a particular emphasis on learning outcomes. The systematic review methodology was used, and our literature search resulted in 33 relevant studies meeting the inclusion criteria. A total of 23 met the minimum quality criteria and were examined in detail (16 reporting positive learning outcomes, 5 no difference and 2 negative learning outcomes). Explanations underlying these observations were analysed, and factors contributing to successful uses of tablets are discussed. While we hypothesize how tablets can viably support children in completing a variety of learning tasks (across a range of contexts and academic subjects), the fragmented nature of the current knowledge base, and the scarcity of rigorous studies, makes it difficult to draw firm conclusions. The generalizability of evidence is limited, and detailed explanations as to how, or why, using tablets within certain activities can improve learning remain elusive. We recommend that future research moves beyond exploration towards systematic and in-depth investigations building on the existing findings documented here.

Publication Journal of Computer Assisted Learning

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Tools like the evidence libraries of the EdTech Hub and Open Development & Education also offer citation trees (Figure 6.4.; ↑Haßler et al., 2024);

however, these are only available for a very limited number of publications, and they are open data. One of the goals of such evidence libraries is to show new research in the context of other publications (↑Haßler et al., 2024). AI tools can support the open generation of such open citation trees, including extracting references, consolidating, and merging reference data. The discussion regarding the above figures illustrates that it is unlikely that any single tool can satisfy all research needs; instead, specific tools need to be chosen for the required tasks.

Citation searching is important, as there is some evidence for its effectiveness (↑Jalali & Wohlin, 2012; ↑Papaioannou et al., 2010). We also note ↑Connected Papers as a web-based tool that can show connections between papers.

Regarding ↑Scite, we note that this tool has been around for several years, and we have used it regularly. It offers a freemium-based model with a free web plugin and a plugin for Zotero; access to the main account requires a subscription. In November 2023, Research Solutions announced the acquisition of Scite (↑Research Solutions, no date). With AI solutions emerging very quickly, other companies and organisations will frequently acquire products, and feature sets will change. For example, Elsevier is adding AI to their Scopus literature search tool (↑Aguilera Cora et al., 2024; ↑Elsevier, no date; ↑Elsevier Products, no date).

New tools are also emerging in the areas of documenting, analysing, and justifying individual search strategies (cf. ↑Templier & Paré, 2018), as well as syntactic search query validation (↑Russell-Rose & Shokraneh, 2019). ↑Wagner et al. (2022) note that this could support researchers in designing and improving different elements of search strategies, including analysis and justification of the scope (publication outlets covered and the selection of search terms in database searches). ↑Sturm & Sunyaev's (2019) paper illustrates how journal coverage reports could enable substantially more targeted and efficient literature searches.

6.3. Screening for inclusion

This step is typically divided into a first (and more inclusive) screening based on titles and abstracts and a second (more restrictive) screening based on full texts (↑Templier & Paré, 2018). The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) approach is staged in this way to make the process humanly feasible.

AI-based tool support for screening has been evolving over the years (↑Harrison et al., 2020), with promising recent progress with AI to screen articles: see 'Human-AI collaboration to identify literature for evidence synthesis' (↑Spillias et al., 2023); 'Breaking through limitations: Enhanced systematic literature reviews with Large Language Models' (↑Reason et al., 2023).

When considering potential AI support for this step, the reliability of manual screening processes should not be overestimated, even if specialists conduct the screening. Recent evidence in the health sciences suggests a base rate of 10% disagreement between inclusion screens conducted independently (↑Wang et al., 2020). This indicates that it may even be possible to augment and improve the screening activities of researchers by having AI-based tools identify inconsistent and potentially erroneous screening decisions.

6.3.1. Taxonomy

The second screening is dedicated to disentangling the remaining cases, which can be particularly challenging since research in education (like climate change mitigation research) is not standardised as strictly as other disciplines. In contrast to the health sciences and biology, for instance, the lack of widely used taxonomies for education/EdTech constructs (or, indeed, climate change mitigation) and lack of standard vocabulary for keywords (contrasting with 'medical subject heading'/MeSH terms) can make it difficult to achieve required classification performance in the second screening (cf. ↑O'Mara-Eves et al., 2015). This challenge applies to humans and machines alike.

We note that EdTech Hub has already made some progress in developing a multi-language keyword inventory that follows appropriate strategies for classifying education research and data extraction (↑Education Endowment Foundation & Durham University, 2022; ↑EPPI Centre, 2003). The inventory allows organising and coding studies based on keywords relating to publication status, geographic focus, curricular focus, and population, etc. (↑Haßler et al., 2019p; ↑Haßler et al., 2021k). Figure 6.5. illustrates an example of this.

In the future, AI may allow moving away from a PRISMA-type, two-stage approach towards more 'spiral approaches'. ↑Saeidmehr et al. (2023, p. 16) note that

> *"lessons learned from training machine learning with title/abstract screening do not necessarily transfer to machine learning that also incorporates PDFs."*

6.3.2. Rayyan

↑Rayyan is a three-tiered subscription, web-based tool that assists with automating literature reviews. It has subscriptions for individuals and teams. The free subscription tier for individuals allows for up to three active reviews with an unlimited number of reviewers but has limited functionality compared to the other tiers. The team subscription plans have no free tier.

↑Rayyan supports the import of citations from a range of reference software. However, it is not integrated with any common reference software, and users need to upload reference files from their local disks manually. ↑Rayyan can automate the detection of duplicate references, allowing users to resolve duplications more efficiently. It allows multiple reviewers to collaborate on one review and enables users to create labels to assist with screening references. ↑Rayyan's AI enables it to help with inclusion/exclusion decisions once the user manually categorises 50 articles. It can generate a probability based on inclusion and exclusion criteria for undecided references for the reviewer to make final decisions. ↑Rayyan also supports collaborative full-text reviews to further assess the suitability of a study in a literature review; it has its own AI chatbot to assist users.

Overall, ↑Rayyan is best described as an AI-supported, semi-automated tool whose main functionality assists with making the screening process of literature reviews more user-friendly and efficient. Beyond this scope, ↑Rayyan has limited functionality.

Figure 6.5. *Extract from EdTech Hub's existing keyword inventory* (↑Haßler et al., 2019p)

Keyword category "TE": terms that include both technology and education							
id	**priority**	**Categories**			**Code**		**Lexemes**
		category	**short**	**sub-category**	**semantic value**	**unique code**	**English**
1	M	edtech	TE	device	electronic whiteboard	electronic whiteboard	electronic whiteboard
2	M	edtech	TE	device	interactive whiteboard	interactive whiteboard	interactive whiteboard
3	H	edtech	TE	device	smart board	smart board	smart board
4	M	edtech	TE	device	smartboard	smartboard	smartboard
5	M	edtech	TE	electronic resour	electronic textbook	e textbook	e textbook
6	H	edtech	TE	electronic resour	electronic textbook	e-textbook	e-textbook
7	M	edtech	TE	electronic resour	electronic textbook	electronic textbook	electronic textbook
8	M	edtech	TE	electronic resour	electronic textbook	etextbook	etextbook
9	M	edtech	TE	electronic resour	Etutor	e-tutor	e-tutor
10	M	edtech	TE	electronic resour	Etutor	Etutor	Etutor
11	M	edtech	TE	electronic resour	free digital resources	FDR	FDR
12	M	edtech	TE	electronic resour	free digital resources	free digital resources	free digital resources
13	M	edtech	TE	electronic resour	Intelligent agent	Intelligent agent	Intelligent agent
14	M	edtech	TE	electronic resour	Intelligent tutoring system	Intelligent tutoring system	Intelligent tutoring system
15	M	edtech	TE	electronic resour	Learning platform	Learning platform	Learning platform
16	M	edtech	TE	electronic resour	massive open online course	MOOC	MOOC
17	M	edtech	TE	electronic resour	massive open online course	MOOCs	MOOCs
18	M	technology	TT	electronic resour	moodle	moodle	moodle
19	M	edtech	TE	electronic resour	open educational resources	OER	OER
20	M	edtech	TE	electronic resour	open educational resources	open educational resources	open educational resources
21	M	edtech	TE	electronic resour	online textbook	online textbook	online textbook
22	H	edtech	TE	electronic resour	Online tutor	Online tutor	Online tutor
23	H	edtech	TE	electronic resour	Reusable learning object	Reusable learning object	Reusable learning object
24	H	edtech	TE	electronic resour	Reusable learning object	RLO	RLO
25	H	edtech	TE	electronic resour	School website	School website	School website
26	M	edtech	TE	general edtech	EdTech	EdTech	EdTech
27	H	edtech	TE	general edtech	EdTech	Education Technology	Education Technology
28	M	edtech	TE	general edtech	EdTech	Educational Technology	Educational Technology
29	M	edtech	TE	general edtech	educational innovation	educational innovation	educational innovation
30	H	edtech	TE	general edtech	Educational technologies	Educational technologies	Educational technologies

6.4. Quality assessment

The quality assessment stage involves checking primary empirical studies for methodological issues, such as sources of bias (↑Higgins & Green, 2008; ↑Kitchenham & Charters, 2007; ↑Templier & Paré, 2018). This step is intended to assess the degree to which the conclusions of reviews aimed at theory testing may be affected by different types of bias (e.g., selection, attrition, and reporting bias). At the time of writing, the potential for AI-based tools supporting these procedures is low to moderate: Assessing (methodological) quality is a challenging task which requires expert judgement, making it difficult to achieve high inter-coder agreement (↑Hartling et al., 2009).

Following methodological guidelines for quality appraisal and risk of bias assessment, researchers conducting meta-analyses and systematic literature reviews can leverage traditional tools like ↑RevManor corresponding packages of statistical software environments like R and SPSS (↑Bax et al., 2007). Further AI-based tools like RobotReviewer (↑Marshall et al., 2015; ↑RobotReviewer) can also be applicable to meta-analyses. While focusing on risk-of-bias assessment of randomised controlled trials in the life sciences, ↑RobotReviewer is an excellent exemplar for explainable AI, allowing researchers to interactively trace ratings in each domain of bias to its origin in the full-text document.

6.5. Data extraction

Data extraction requires researchers to identify relevant qualitative and quantitative data fragments and transfer them to a (semi) structured coding sheet (↑Templier & Paré, 2018). It is more salient in descriptive reviews, scoping reviews, and reviews aimed at theory testing than in more selective and interpretive reviews, such as narrative and theory development reviews.

Tools used in this area, such as ↑ATLAS.ti and ↑NVivo, are implementing Natural Language Processing and machine learning algorithms for tasks such as automated qualitative coding, named entity recognition and sentiment analysis (AI in ATLAS.ti: ↑ATLAS.ti, no date; AI in NVivo: ↑Lumivero, 2023). There are also specialised tools for extracting data from tables or statistical plots, such as ↑WebPlotDigitizer.

In 2015, in the health sciences, which have established relatively consistent reporting practices, corresponding tools designed to extract study characteristics like the PICO (population, intervention, context, and outcome) elements were still in the early stages of development (↑Jonnalagadda et al., 2015). However, this is a significant focus for emerging tools (such as ↑Elicit), and rapid progress is possible.

In the domain of information science, ↑Wagner et al. (2022) envision enhancements of databases and complementary repositories to facilitate AI-based literature reviews. There is a similar need in education research. In particular, the question arises as to why it has not been possible to construct databases with relevant extractions. Currently, key descriptive information (such as PICO) is not reported in machine-readable formats, let alone a common metadata format for research features. Therefore, literature reviewers extract such information manually. Such extractions would not fall under copyright protection and could be shareable. Indeed, across their portfolio of review and meta-analysis, the Education Endowment Foundation requires that commissioned work aligns and contributes to their internal databases. See Section 7.1. for further discussion.

6.6. Data analysis and interpretation

The final step of the review process can take various forms, depending on the type of review (↑Templier & Paré, 2018). Different tools are available depending on the main knowledge-building activities (↑Schryen et al., 2020). For descriptive syntheses, there is a range of established tools for text-mining (↑Kobayashi et al., 2017), as well as tools for analysing and visualising topics, theories, and research communities based on scientometric techniques, computational techniques, or Latent Dirichlet Allocation models (↑Balducci & Marinova, 2018; ↑Nakagawa et al., 2019; ↑Thilakaratne et al., 2019), for instance. In assessing the potential for future AI-based tools to support data analysis, we need to consider that this step can take various forms. In pre-theoretical reviews, AI-based tools offer capabilities to generate descriptive insights, for example, based on topic modelling (↑Kunc et al., 2018; ↑Mortenson & Vidgen, 2016; ↑Schmiedel et al., 2019) and ontological annotation (↑Huettemann, 2023).

6.7. General observations

This subsection includes general observations about all AI tools when used in LMIC contexts. While AI tools offer efficiency and breadth for literature reviews, there are additional limitations when dealing with the diverse and complex educational landscape of LMICs compared to what AI offers for research in high-income country contexts.

- **Representation and accessibility of data:** In LMICs, there is a notable under-representation of education research in major digital databases, which are the primary sources for AI-driven literature reviews. This leads to an incomplete understanding of the education landscape in these regions. The development of education systems using AI often lacks emphasis on presentation methods or data mining, focusing instead on logical modelling, which may not fully capture the complexity of education contexts in LMICs (↑Zhai et al., 2021).
- **Language and cultural barriers:** AI tools are generally optimised for English and may not accurately interpret or analyse research published in local languages or dialects of LMICs. This limitation can lead to significant gaps in understanding and integrating cultural contexts and nuances, which are vital for comprehensively reviewing education research in these regions. For example, the use of AI tools, like ChatGPT, in higher education, has raised concerns about cultural bias in generated responses and the need for more linguistically and culturally diverse training data. This reflects the challenges of AI in accurately representing and understanding the nuances of different cultures, particularly in LMICs where cultural diversity is significant (↑Atanasova, 2023).
- **Bias in AI algorithms:** AI algorithms are prone to biases present in their training data. Since AI development is predominantly concentrated in high-income countries, there is a risk that these tools may not be attuned to the specific educational challenges, methodologies, or priorities in LMICs. This bias can skew the literature review towards perspectives and contexts more commonly found in high-income countries. Furthermore, AI language tools can pose a risk to scientific diversity and innovation. The dominance of English in scientific publishing, aided by AI language tools, may marginalise non-English research and researchers, which is particularly relevant in LMICs where English is not the primary language (↑Nakadai et al., 2023).
- **Complexity of local educational issues:** The unique and complex educational challenges LMICs face may not be fully understood by AI tools. For instance, integrating AI in education systems in LMICs often requires a deeper understanding of hierarchical structures and local nuances, which AI may not adequately address (↑Zhai et al., 2021).
- **Ethical and privacy concerns:** Ethical concerns arise in the use of AI for analysing sensitive educational data in LMICs. Issues related to

consent, privacy, and data governance are particularly pressing in these contexts, where standards and regulations may vary significantly from those in high-income countries.

- **Dependency on technology and expertise:** Over-reliance on AI for literature reviews can lead to a lack of critical human engagement with the material, which is crucial in education research where contextual understanding is vital. Additionally, the implementation of AI tools in LMICs is limited by resource constraints, including the need for technical expertise and infrastructure. For example, integrating AI tools in teaching English as a Foreign Language (EFL) highlights the dependency on technology and expertise (↑Rebolledo Font de la Vall & Gonzalez Araya, 2023). AI-powered tools offer personalised learning and real-time feedback but underscore the need for technical know-how and infrastructure to implement and utilise these technologies effectively. This dependency poses a significant challenge in LMICs, where resources and expertise in AI may be limited (↑Rebolledo Font de la Vall & Gonzalez Araya, 2023).
- **Rapid evolution of the AI field:** AI research is rapidly evolving, and reviews may miss relevant new research published after the database search. This is particularly relevant in LMICs, where ongoing research might not be immediately available in major databases or might be communicated through channels not typically monitored by AI tools (↑Ciecierski-Holmes et al., 2022).

7. Outlook

↑Wagner et al. (2022) outline an agenda suggesting how information science researchers can focus and coordinate their efforts in advancing AI for literature review. They note that nurturing this endeavour is a task for the entire scholarly community, including a broad range of researchers, methodologists, reviewers, journal editors, and authors of primary research papers. We recommend reviewing the recommendations by ↑Wagner et al. (2022).

We close by highlighting some areas that pertain closely to this topic brief, with reference to initial recommendations made in Section 2.3.6. above.

As noted above, a significant issue is the absence of comprehensive databases, and there are currently no existing commercial products that deliver on literature reviews for education / EdTech in LMICs. To make headway and move forward in this area, we consider two areas.

7.1. Convene stakeholders

The purpose of this convening would be to make evidence available, index it systematically, and explore AI collaboratively to maximise outcomes and reduce costs. As noted above, a significant challenge is the collation of relevant literature into appropriate databases. One could consider building a network with stakeholders to coordinate and synthesise efforts. Such stakeholders could include BE2, the Education Endowment Foundation, Education Sub Saharan Africa (ESSA), Campbell, eBaseAfrica, J-PAL, What Works Clearinghouse, Cochrane, 3ie, OpenAlex, Open Development & Education, researchers from the Global South and selected universities from the Global North, as well as community efforts (e.g., the evidence synthesis hackathon, ↑Haddaway, no date). A few of the above stakeholders are already working together to determine more systematic ways of sharing evidence, shared ways of extracting data from evidence to speed up literature review and meta-analysis, etc. Overall, many structured low-cost approaches are readily available to get more evidence into circulation (such as Crossref DOI allocation).

7.2. Undertake in-depth exploration of AI tools

In this topic brief, we have highlighted several promising tools and approaches that appear very promising to accelerate rigorous evidence synthesis. Given the limitation of the majority of the current very-easy-to-use web-based tools, it would appear beneficial to undertake an in-depth exploration. This exploration could include an extensive trialling of ↑EPPI-Reviewer and ↑ASReview, including some workshops for researchers from LMICs, to explore barriers to using those tools.

It would also be interesting to undertake a coverage assessment of the ↑OpenAlex dataset. This would help to understand the data quality (as provided by various organisations), with a view to making recommendations for improving data quality. This activity could extend into topic modelling within the ↑OpenAlex dataset. ↑OpenAlex also categorises publications according to the Sustainable Development Goals (↑UN, no date), which could be extended and tailored to the needs of education / EdTech within LMICs, perhaps producing a living review.

7.3. Conclusion

The two activities mentioned above would allow for an informed, evidence-based pathway towards the better use of AI tools to help identify, review, and synthesise evidence for literature reviews for education / EdTech in LMICs.

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This bibliography is available digitally in our evidence library at https://docs.edtechhub.org/lib/BVD8JX7V

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