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The Present and Future Landscape of AI in Scholarly Publishing

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Introduction

This report responds to a request for a survey of the current landscape of artificial intelligence (AI) in scholarly publishing, with a consideration of benefits, challenges, and emerging opportunities, and including evidence, examples, practices, and tools. It obviously falls short of that remit but represents a best effort in that direction.

The report has been divided into two major sections, the first being a high-level overview of the benefits, challenges and opportunities offered by AI in scholarly publishing, and the second being a deeper but more focused dive looking at examples, practices, evidence, and tools. Both sections are characterized by both a wealth and paucity of materials; the literature is rich with discussion, but it remains tantalizingly difficult to find solid ground on which to land.

The request naturally formed the content for search parameters, and various versions of these were used to find resources through Perplexity, Google Search, Kago, and Google Scholar (tools typically used by the author). The scope was far too broad for anything like a structured literature review, and it is not clear that in such a rapidly changing domain research based on aggregation would be sufficiently reliable.

Searches were limited to resources published in the last two years; even so, out-of-date content was frequently encountered, especially in scholarly publications, where the publication cycle is slower than the pace of change in the domain being studied. When appropriate, references and secondary discussions were followed to expand on search results.

It is worth noting that the search methodology employed resulted in the surfacing of far more than scholarly publications; this means some reports must be taken with a degree of skepticism, but by the same token, there is a freshness and closeness-to-the-field that is not possible when relying on academic publications alone. In any case, the credibility of each resource was assessed, and any reason for doubt was mentioned.

The organization and categorization of the material was performed by hand by the author through the process of reviewing the literature; the original research notes are [available online](#). The authoring of the report text, also performed entirely by hand (in Microsoft Word), represents a second pass through the material, allowing additional identification of trends and limitations.

Benefits, Challenges, and Emerging Opportunities

Artificial intelligence is not a single-faceted development. It offers a number of potential benefits to researchers and journal publishers, while at the same time posing a series of challenges alongside opportunities that may change the nature of scholarly publishing altogether.

Benefits

Most significantly, “AI can reduce operational costs and democratize access to academic resources” (Engelhardt, 2025, para. 3).

The majority of researchers say that it’s helped them in many aspects of their work. 85% of researchers using AI report that it has helped their efficiency, while close to three-quarters say that it’s helped them with the quantity (77%) and the quality (73%) of their work. 70% also find it valuable for brainstorming and ideation, and 61% for improving their ability to focus on their most important tasks. (Wiley, 2025, p. 5)

Based on a systemic literature review, Khalifa and Albadawy (2024, from Table 1, p. 3) outlined six domains where AI can improve academic functions:

- idea development and research design
- literature review and synthesis
- content development and structuring
- data management and analysis
- editing, review, and publishing support
- communication, outreach, and ethical compliance

Research Design

Research design can be a complex process that varies according to discipline and context. At the same time, research methodology has been extensively documented, and thus AI chatbots can help generate structured questions, map the problem space, and develop alternative framings (Kibuacha, 2026).

Even if instructions are vague and the research objectives are unclear, a typical large language model such as ChatGPT can provide a detailed research plan in a few seconds. Here is an example of a [one-sentence prompt and detailed output from ChatGPT 5.2’s general model](#). This sort of output can be essential to research design and yet would disappear in the subsequent documentation of that research (unless it was used to generate additional elements).

Literature Reviews

“AI chatbots may be used to draft literature reviews and introduction sections of manuscripts, design experimental protocols, and perform data analysis,” writes Mokkaiki (2024, p. 2). This activity ranges from determining what to research (Wiley, 2025, p. 22) to “the application of AI techniques in the semi-

automation of systemic literature reviews (SLR), within the two main stages of application, namely screening and extraction” (Bolaños et al., 2024, p. 2).

Content Creation

Generative artificial intelligence (GAI) is perhaps best known for authoring content on request, though it offers a range of supports in the content creation process, including:

- **Writing:** use of chatbots to write articles. “In some cases, the resulting text is indistinguishable from what people would write” (Brainard, 2023, para. 4).
- **Wordsmithing:** “A major attraction of AI is the automation of ‘wordsmithing’; the process and technique of composition and writing.” (Clark et al., 2024, p.1)
- **Metadata generation:** See Ajakaye and Pendergast (2024).

Data Management and Analysis

Advanced data management can be a challenge for researchers without a deep technical background, but AI makes these tools and techniques widely accessible. A few specific examples of data management and analysis include:

- error and bias detection (Wiley, 2025)
- analysis of complex documents, for example, the AI-generated [Compilation of STM Publisher Policies](#) (Mollaki, 2024)
- processing unstructured data (Wiley, 2025)

Editing and Review

While there has been considerable debate regarding the use of AI to generate peer reviews (Mayers, 2025), there are uses of AI in other aspects of the editing and peer review process, especially editorial review, including correcting grammar and other errors (Simis, 2025; Wiley, 2025) as well as verifying citations (Haan, 2025).

AI also assists with the managerial aspects of journal editing and publication, such as reviewer assignments. Supporting this, for example, Álvarez-García et al. (2026) described open researcher and contributor ID-integrated retrieval, large language model (LLM)-based semantic similarity, and evaluation of aggregation strategies.

Communication and Outreach

For academic journals, publishing an issue is only one part of the public outreach process (though AI can help with that as well). For example, AI can help a publisher generate indices, rethink Hirsch index and similar author metrics (Dragos, 2025), and calculate journal impact.

AI can also make the journal more accessible. Lou Peck (The International Bunch) emphasizes that AI can create “simplified summaries, translations, videos, and infographics making complex research more

understandable to a broader audience” (Simis, 2025, para. 12). AI can also generate social and commercial media placement, optimize search engines, and manage newsletters.

Challenges

Like any new and powerful technology, artificial intelligence has its detractors, and they have often reasonably pointed to a number of practical, social, and ethical issues around its adoption and use. These challenges are all passed on to any organization dealing with the arrival of AI in its domain.

For the section that follows, though, we will not attempt a survey of all known objections to and issues raised by AI. There’s a long analysis in my *Ethics, Analytics and the Duty of Care* [course](#) and [article](#). For this report we focus specifically on the challenges that arise within the context of academic journals.

Accuracy

In any discipline, journals are the publication of record, documenting progress and advances in research. As such, the accuracy of this record is a primary concern, both with reference to authorship, attribution, and historical data, as well as potentially novel statements of fact that may appear in new articles.

The well-documented issues around accuracy raised by the use of AI are of significant concern. “More researchers are worried about potential inaccuracies and hallucinations—this year, 64% of researchers” (Wiley, 2025, ‘Key Findings’, para. 4).

Particularly troubling has been the corruption of the academic record. “AI-generated citations to non-existent sources have penetrated the bibliographies of peer-reviewed publications” (Glynn, 2026, p. 2).

Research Integrity

Research integrity can be defined as “the conduct of the research process ethically, with honesty, robustness, and transparency when proposing, conducting, evaluating, and reporting research findings” (Catharina et al., 2024, p. 1). The mere existence of AI, whether it works well or not, raises this issue.

There is a clear danger of the ‘publish or perish’ culture trumping scientific integrity . . . threats to research integrity have come to the fore and multiplied now that artificial intelligence (AI) is fast being integrated into research (see literature review). (Nicholas, Herman, et al., 2025, p. 14)

AI can churn out loads of text that look like scientific papers but lack substance or scientific rigour. Paper mills use this technology to produce a high volume of low-quality articles, publishing them without proper review or oversight. This undermines the credibility of scholarly publishing and spreads unreliable scientific information. (Nicholas, Herman, et al., 2025, p. 14)

Ethical Issues

Numerous ethical issues have been raised regarding AI in publications, including the following:

- **authorship and ownership:** LLMs challenge traditional notions of intellectual ownership, raising questions about proper attribution and originality (Stokel-Walker, 2023). It is widely argued that an AI itself cannot be an author, but in such a case, where does the credit lie?

- **bias and fairness:** AI-generated content may perpetuate harmful biases embedded within training datasets, and this bias may infiltrate research design, results, and publication.
- **privacy and consent:** “LLMs trained on vast, often unregulated data sources introduce significant privacy risks” (Almufarreh et al., 2025, p. 2).

Technical Readiness

Without entering the depths of technology readiness literature, it seems clear that this question faces the entire domain, including authors, editors, reviewers, and publishers. In addition, it is not yet clear that AI is technologically ready for the complex tasks involved in academic publishing. “According to the Technology Readiness Level scale (Defence Science and Technology Group, 2021), the LLMs-based innovations are still in the early development and testing stage” (Yan et al., 2023, p. 97). Despite significant advances, this remains true today.

Technical readiness raises issues already faced by journals even before AI. “The key factors identified were mainly related to organizational information technology infrastructure, top management support, resource availability, collaborative culture, organizational size, organizational capability, compatibility, data quality, and financial budget” (Ali & Khan, 2024, p. 226). AI-specific challenges are more numerous than other factors.

Opportunities

In this report, we have defined opportunities differently from benefits as were discussed above. While benefits describe how scholarly journals operating in a traditional manner may reduce costs, improve the product, and function more effectively, this section on opportunities points to possible transformations of the traditional academic publishing paradigm that may occur.

Thus, just as some readers may have thought the challenges section immediately above was insufficiently broad, leaving out, for example, existential risks faced by journals in the light of the new technology, such as abandonment by readers, swamping by AI-generated content, or diversion of funding and support, this section represents the other face of that discussion, describing possible—and even likely—changes that will be made by journals in response to AI.

We cannot be comprehensive here; with each new day additional opportunities present themselves, while at the same time other opportunities are overtaken by developments in AI and publishing. What follows below is no more than a snapshot of what is possible.

Expanded Accessibility

When we think of accessibility, we usually think of reading aids such as translation or text-to-speech, but in this section, we have considered improved accessibility to the academic writing and publishing process itself.

In its own work on AI in publishing, Wiley (the company) has described a host of research support services that AI could offer potential authors:

- formatting manuscript to comply with submission guidelines
- detecting errors or bias in own writing
- monitoring/summarizing key new publications in your field of study
- checking own work for unintended plagiarism
- reviewing large amounts of published and pre-print studies
- writing assistance (e.g., copyediting, translation)
- creating plain language summaries of article findings
- generating reference recommendations
- identifying key themes in existing published literature
- building a custom library of information tailored to your area of study (Wiley, 2025)

The upshot of these services is that they make publishing easier for researchers, especially early career researchers, and this support allows even people outside the traditional domains of academia and research institutions to participate in and contribute to the scientific research process.

AI-Augmented Peer Review

The subject of AI and peer review is being discussed in a sibling report in IRRODL from Aras Bozkurt, so we won't examine it in detail here. That said, AI support for peer review includes:

- identifying peer reviewers with relevant expertise
- adapting reviewer feedback into standardized format
- helping peer reviewers adjust tone and clarity of feedback
- increasing speed and ease of peer review
- helping peer reviewers validate sources and claims
- providing step-by-step guidance to peer reviewers
- peer reviewer recommendation tool based on article comparisons
- automated feedback to reviewers to ensure clarity in reviews (Wiley, 2025)

It is important, in my view, to extend our understanding of peer review, and therefore AI-supported peer review, beyond the traditional context of pre-publication peer review of human authors. At a certain point, large volumes of AI-generated social and scientific research will be generated, and there is a need to review this. It won't be possible for humans to undertake this work because of the volume, and yet it may fall to journals (or their inheritors) to define metrics, systems, and processes for this.

Citations

Citations serve multiple purposes in academic literature though this is not always clear or evident in practice. These purposes include acknowledging sources, giving credit, establishing credibility, supporting

claims and evidence, legal cover, and building academic reputations—both yours, and the people you cite (Wong, 2024).

Yet these objectives are sometimes at cross-purposes: I may read something (like this list) in a blog, using that to inform my content, though the blog itself may not be academically worthy (though MyBib, which I'm using to record citations, lists it as probably credible).

The substantial increase not only in the number of researchers, increasing competition, along AI-assisted and generated publication, but also a number of new research formats (discussed below), makes the practice of citation even more fluid.

Here's where it stands now.

Citations are all-pervasive, although cropping up mostly in the reputational and trust arenas. Citations remain a major force in determining what is read, where to publish and what to trust. There are no signs their value is diminishing; if anything, the opposite is true. AI has given a boost to their use—primarily as a validity check. There are strong signs that altmetrics are being taken up. (Nicholas, Abrizah, et al., 2025, p. 1)

Alternative Publishing

New AI technologies give journals the opportunity to consider alternative models of publication. These alternatives, on the one hand, respond to challenges posed by the technology, and at the same time, leverage the capacity of AI. This by itself could be a single focus of investigation; for now, we have a number of possibilities:

- **idea registries:** “Instead of formatting every thought into a formal paper, let researchers log ideas, hypotheses, or models as lightweight entries. Something between a sketch and a full manuscript” Kumar (2026, para. 16).
- **disaggregating publication:** One of the most interesting examples of this is Octopus, “a new publishing platform for scholarly research. Funded by UKRI—the UK government research funder” (Octopus, 2026), designed to stage and recognize contributions to each part of research publications
- **contribution maps:** “Imagine a visual map of how research builds on research — not just who cites whom, but how ideas evolve. It would make influence visible in a way that a citation list never could” (Kumar, 2026, para. 17).
- **multi-modal publications:** An example is the [Claude Code Guide](#), a resource that contains “20K lines of documentation, 175 templates, 274-question quiz, security threat database (24 CVEs), and TDD/SDD/BDD workflows.” It was developed using AI and is made available as free and open-source content on GitHub.

- **living documents:** “Think of a paper that updates over time with transparent version history. This reflects reality far better than a one-shot ‘final’ draft” (Kumar, 2026, para. 18). Similarly, “some of Springer Nature’s reference works are published as [living references](#) which are online first, real-time snapshots (article collections) of a reference work which is in development or is being updated” (Springer-Nature, 2025, para. 1).
- **open community review:** “Instead of a single round of anonymous peer review, think open commentary, visible revisions, and community endorsements. Credibility grows in public, not behind closed doors” (Kumar, 2026, para. 18).
- **impact-based recognition:** Instead of rewarding the number of publications, reward how much an idea changes a field. Replication, reuse, extension are better signals than raw volume. All quoted from Kumar (2026).

New Products

“LLMs-based innovations have already shown high performance on several relatively simple classification tasks” (Yan et al., 2023, p. 97), and this is just one of the capabilities that creates opportunities for journals to offer new products. Articles and parts of articles, for example, can be classified and reorganized by any number of criteria facilitated by AI-classification services.

Zhou (2025) suggested the possibility of a number of so-called premium products including research assistants, institutional dashboards, and personalized discovery environments—framed as value-added services for libraries and funders (Zhou, 2025). A number of these are already offered in some publisher products (see below).

Some disciplines and research areas will themselves be digitized. A good example of this is computational social science, which employs AI tools and methods to support things like population studies, structured reviews, and document analysis (Lazer et al., 2009). “Computational methods allow us to sift through massive data to find the scientifically relevant pearls” (Lazer et al., 2009, p. 721).

The tools employed in disciplines such as computational social science could become a future list of offerings from journal publishers.

Computational social science research often seeks to model and predict the behavior of complex systems. Simulation techniques provide a flexible way to examine how collective behavior emerges from individual decisions, transactions, and structural factors. Agent-based simulations, which model larger structures arising from the actions and interactions of autonomous agents. (Lazer & Ognyanova, 2024, p. 3)

Evidence, Examples, Practices, and Tools

If the preceding section offers a view of the landscape, mapping major routes and divisions, this next section offers a view of the terrain, offering more focused looks at some of the on-the-ground realities of AI in scholarly publishing.

If there is an overall trend that could describe this part of the report, it is that it is incomplete, not only because of limitations of scope and methodology, but also because much of the necessary exploration has not yet been undertaken.

Evidence

The major trend with respect to evidence is that it is limited. The now nearly-ubiquitous large language models in use today were introduced only in 2022; there has not been time to gather a great deal of evidence regarding use, affordances, or other factors.

Use of AI

To paraphrase Wittgenstein, the meaning of something lies in how it is used. Probably the most telling of any evidence has been findings that show “far more authors use AI to write science papers than admit it” (Brainard, 2025).

“Detection of AI-generated text in all 3 sources (abstracts, methods sections, and reviewer comments) started increasing dramatically beginning in Q1 2023 after the public release of ChatGPT in November 2022” (Evanko & Di Natale, 2025, para. 3 (“Results”)).

Numerous other studies have identified widespread and growing use of AI tools across most scholarly disciplines.

Risks

A large number of articles, though mostly polemic, have pointed to the risks of depending on artificial intelligence for substantial parts of the research and content publication functions. At this point, most of the evidence consists of single cases and anecdotes.

In historical policy debates (e.g., over tobacco ca. 1965 and fossil fuels ca. 1985) “evidence-based policy” rhetoric is also a well-precedented strategy to downplay the urgency of action, delay regulation, and protect industry interests. Here, we argue that if the goal is evidence-based AI policy, the first regulatory objective must be to actively facilitate the process of identifying, studying, and deliberating about AI risks. (Casper et al., 2025, p. 1)

Capabilities

Evidence describing the capabilities of AI and LLM systems is more prevalent and often based on the performance of specific systems against industry-standard benchmarks. “Key recommendations emphasize local validation using independent datasets, selecting task-specific metrics, and considering deployment context to ensure real-world performance matches claimed efficacy” (Klontzas et al., 2025, p. 1).

AI capabilities vary from model to model and across different specializations. For example, in radiology, “key performance metrics, including overlap metrics for segmentation, test-based metrics (e.g., sensitivity, specificity, and area under the receiver operating characteristic curve), and outcome-based metrics (e.g., precision, negative predictive value, F1-score, Matthews correlation coefficient, and area under the precision-recall curve)” (Klontzas et al., 2025, p. 1).

Capabilities can also be measured in terms of cost. For example, in

an innovative approach that uses artificial intelligence to streamline the screening process for systematic reviews. . . Where single human abstract screening was estimated to require more than 83 hours and \$1666.67 USD, our LLM-based approach completed screening in under 1 day for \$157.02 USD. (Cao et al., 2025, para. 7 ‘Results’)

Most available evidence regarding AI performance shows continually increasing capabilities, though evidence specifically related to scholarly publishing is lacking.

Examples and Practices

The examples described in this section focus on how journals are adapting to and working with AI, while specific tools and applications are described in the next section.

Policies

It has become common for journals to adopt policies regarding the use of AI-based tools by editors, reviewers, and authors. These can include disclosure requirements (see below) and “at least one publisher has taken a tougher line: the Science family of journals announced a complete ban on generated text last month” (Brainard, 2023, para. 7).

There is a compilation of [STM Publisher Policies](#) regarding authors’ use of AI to assist in the research process (Mollaki, 2024). Major publishers and ethics bodies (e.g., Committee on Publication Ethics [COPE], World Association of Medical Editors [WAME]) have converged on three points: (a) chatbots cannot be authors; (b) authors must disclose AI use in writing, figures, or analysis; and (c) humans must remain responsible for all content.

AI Declaration and Disclosure

It has become common for journals to require that authors declare in some degree of detail the use of artificial intelligence in preparing the publication.

Policies require that authors disclose use of text-generating tools and ban listing a large language model such as ChatGPT as a co-author, to underscore the human author’s responsibility for ensuring the text’s accuracy. That is the case for Nature and all Springer Nature journals, the JAMA Network, and groups that advise on best practices in publishing, such as the Committee on Publication Ethics and the World Association of Medical Editors. (Brainard, 2023, para. 7)

For example,

Heliyon, a Cell Press journal, states the following in their guide for Authors: The use of generative AI and AI-assisted technologies in scientific writing must be declared by adding a statement at the end of the manuscript when the paper is first submitted. The statement will appear in the published work and should be placed in a new section before the references list. An example:

- Title of new section: Declaration of generative AI and AI-assisted technologies in the writing process.
- Statement: During the preparation of this work the author(s) used [NAME TOOL/SERVICE] in order to [REASON]. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

The declaration does not apply to the use of basic tools, such as tools used to check grammar, spelling and references. If you have nothing to disclose, you do not need to add a statement. (Resnik & Hosseini, 2025, pp. 7–8)

Human-Autonomy Teaming

Human-autonomy teaming (HAT) “has been described as at least one human working cooperatively with at least one autonomous agent, where an autonomous agent is a computer entity with a partial or high degree of self-governance with respect to decision-making, adaptation, and communication” (O’Neill et al., 2020, p. 904). HAT processes have been described in numerous disciplines, some including academic publication.

For example, a process known as dyadic epistemic dialogue “is a recursive method of scholarly knowledge generation in which a biological author and a non-biological epistemic agent (such as a large language model) engage in structured, bidirectional reasoning to transform, refine, and stabilize epistemic content and focus of an AI model unlike any previous model or technique” (COPE, 2025).

Use Cases

Helen King is in the process of compiling a list of [AI-powered publishing use cases](#) (King, 2026). This remains a work in progress and has not been verified, yet is already comprehensive and plausible. The use cases are sorted by area, such as advertising or author support, associated with a specific publisher or company, and supported with a brief description. Examples include ‘Hum Alchemist AI Content Tagging for Us Weekly’ by A360Media or ‘Keyword Recommendation Services (KRS)’ by Molecular Communications.

Governance and Ethics

Publishers in general are wrestling with questions of governance and ethics, with discussion being voluminous and wide-ranging. Issues include (a) the tension between efficiency and integrity (one can consider the popularity of two-week review turnarounds); (b) the potential for bias and hallucinations; and (c) the risk of loss of trust if journals are not governed with clear policies, robust oversight, and transparent communication to authors and readers.

There are also cultural and equity concerns. Numerous authors have pointed to the risk of dependence on proprietary models, the potential for AI to expand the digital divide via unequal access to cognitive resources, and the potential marginalization of non-English or non-mainstream scholarship if review and publication models are not carefully trained.

Many more issues can be found in discussions and policy papers. A sampling (COPE, 2025) includes the (a) questions that arise around enforcement of standards, (b) how policies can remain agile and adapt to new

tools and methods, (c) policies and practices around the use of AI-detection technology, and (d) the observation that “what we are seeing is a system that desperately wants to benefit from AI’s efficiencies (in peer review, formatting, copyediting), but wants to control or suppress its use when initiated by scholars—especially those outside elite, Anglophone institutions” (COPE 2025 web page, Viktor W comment, 11 June 2025, 14:48 BST, part 4, para. 2).

Tools

Publisher Tools

Major publishers have followed the lead of other application providers (such as browsers and word processors) and have integrated AI into their existing toolsets for authors and editors. The following is a summary of major publisher suites.

[Scopus AI](https://www.elsevier.com/products/scopus/scopus-ai) “combines trusted, peer-reviewed content with sophisticated AI to deliver faster, deeper insights. Built for academic workflows, it accelerates discovery, identifies patterns and supports strategic thinking, all while championing academic rigor” (Scopus AI website, as of June 21, 2026, <https://www.elsevier.com/products/scopus/scopus-ai>).

According to de Leon et al. (2025)

Scopus AI may be biased and promote Elsevier journals. Currently, there is no way of knowing which journals’ copyrighted texts have been excluded for training Scopus AI. . . . The authors assume that none of the other 4 large scientific publishers (Black & Wiley, Taylor & Francis, Springer Nature and SAGE) could develop a system to compete with Scopus AI, as they lack large databases of article abstracts such as Elsevier has. (p. 438)

Springer Nature launched Curie, an AI-powered scientific writing assistant in 2023 (Springer-Nature, 2023) and rebranded it as Rubriq in 2025. “Rubriq uses advanced artificial intelligence and natural language processing algorithms to assist you in editing and translating scholarly writing. Rubriq analyzes the input provided by users and suggests edits, helping with tasks like drafting articles, polishing grant applications, or improving writing style.” (Springer-Nature, 2025, para. 2)

Perplexity: “In 2024, Wiley partnered with the AI-powered search engine Perplexity, integrating Wiley’s academic content into Perplexity’s Enterprise Pro platform. (Kiss, 2025, para. 2).

Content Clarity from DCL provides a deep analysis of a publisher’s entire catalog to answer these questions and many more. We audit and generate insights that allow organizations to view a collection based on specific content metrics. The Content Clarity Report illustrates where you have issues or errors in XML files, metadata, DOIs, xrefs, and more. (Data Conversion Laboratory Inc., 2026, para. 1)

Editor/Review Tools

There are a number of standalone tools designed to support editors and reviewers. Examples include Paperpal and Draftsmith for editing and ScholarOne for workflow management. This is a fluid and rapidly

changing marketplace; [Reviewer Credit](#) offers a list (though it's probably out of date and possibly AI-generated).

Researcher/Writing Tools

Numerous tools for researchers and writers exist; these are often quite specialized. For example, Bolaños et al. (2024) analyzed 21 systemic literature review tools. More tools are listed in [a guide from King's College](#).

There is also a general tools list from the [University of Manitoba](#). Additional writing tools include [Rubriq](#), [Paperpal](#), [Trinka.ai](#), [Hemingway Editor](#), [DeepL](#), Write, and [Notion AI](#).

Communication and Distribution

Many tools exist to support distribution, injection into social media, and search engine optimization, though these are not aligned specifically to the needs of scholarly publications. Still, this is an area that has been explored by commercial publishers.

[ScienceOpen](#), for example, “is the framework that connects every stage of your research communication—from early results to peer-reviewed publication. In a fragmented publishing landscape, we offer researchers a coherent, open system that supports visibility, credibility, and lasting impact”

In this category, it is also relevant to mention the publication facts label (Willinsky & Pimentel, 2025) designed analogously to an ingredients label to describe how the contents of the publication are generated.

A Note on Tools

This section has been unavoidably sketchy, since it could take a very long time to identify and categorize all extant AI-based tools relevant to scholarly writing and publishing. It would also not be the best use of one's time.

One of the major implications of new LLM applications is that users can author their own tools. For example, people are authoring their own RSS (Really Simple Syndication) readers, teaching assistants, course-authoring tools, and writing support tools. It is very likely (though not yet shown) that AI has been used to author editing, citation-checking, and validation tools. It would be arguably faster to ask Claude Code to create an article-reviewing tool than it would be to review an individual article, with results that are comparable.

Recommendations

In this section we do not offer a set of recommendations for readers, as may be typical for a report such as this, but rather focus on the sorts of recommendations made by others writing on this topic. There is considerable overlap among them.

AI Use

“Transparency as default: normalize the disclosure of AI use” (Baldwin & Borchert, 2026, para. 26, point 1). Some forms of use (such as AI-authored publications) should be banned while other uses should be disclosed (European Association of Science Editors, 2025; Flemmyng et al., 2025; Resnik & Hosseini, 2025).

Search

AI in general and large language models in particular represent an advance beyond facet-based or keyword searches. Hence, it represents a natural add-on for publications.

Accessibility

Journals are recommended to take advantage of AI to improve accessibility and multi-language coverage (Simis, 2025).

Human Judgment and Voice

AI tools should support, but not replace, human judgment (Eren & Perez, 2025; Simis, 2025). Authors should be held accountable for their claims. Also, “favor authentic voice over algorithmic polish” (Baldwin & Borchert, 2026, para. 27, point 3). Similarly, “evidence synthesists are ultimately responsible for their evidence synthesis” (Flemyng et al., 2025, summary, point 1).

Usage and Design

Consider new models of publication and new metrics to measure reader engagement (Simis, 2025). “Assess your readiness—both culturally and structurally—to adopt a new paradigm for a particular problem or context” (Hill & Marshall, 2025, para. 49, point 2).

Relation Between People and AI

“The path forward, for now, is neither uncritical automation nor status-quo skepticism, but a mixed-initiative paradigm in which AI augments and never replaces human judgment” (Eren & Perez, 2025, p. 4).

Discussion and Conclusion

The preceding is a very brisk summary of the nature and impact of artificial intelligence on scholarly publishing. Even so, the scale of the impact is demonstrated by the length of this report.

There are clear limitations. The report was authored in a short time; it is not a systematic review of literature (even assuming an SLR would be an appropriate methodology for this topic), and is in many places only a surface assessment of discussion and findings. As a map, it suffers the defect of all maps: it is not the territory. The strong lines drawn in the first section are fluid and changing; the terrain described in the section is a snapshot at best.

In this there is a danger that the major message of this report has been understated: the arrival of artificial intelligence will have a substantial impact on journal publication. This article—which surveys existing examples, practices, and tools—can only provide a snapshot. Far more important is the wider trend, which sees new practices being developed at every point of the research publication process. That is why not only are AI trends useful, so are trends that also challenge the model of publishing itself, such as the Octopus project.

A full understanding of the impact on AI in scholarly publishing needs to be preceded, I think, with a consideration of the goals of publishing itself. We considered the question above when discussing citations: are we recording a conversation among academics, providing a version of record to entrench scientific

findings, supporting discovery and search processes, or something else? Many parts of the scholarly paper (for example, perhaps, the literature review) may not be necessary in a densely interconnected web of scientific reports and findings.

Perhaps the journal should be something else entirely. Perhaps one part of it could function as a pre-registration of empirical research (Field et al., 2020) with another part devoted to replicating previous results, and yet another for theoretical integration (assuming we have a common understanding of the role of theory in an era of mass data).

This report, therefore, should represent only the beginning of a discussion of what the purpose of a journal should be, the tools and methods that can be employed to achieve that purpose, and the safeguards and risk management necessary to ensure the success of that mission.

References

- Ajakaye, J., & Pendergast, N. (2024, May). AI generated metadata for equitable publication access. *Society for Scholarly Publishing 47th Annual Meeting*. <https://doi.org/10.14293/s2199-ssp-am24-01025>
- Ali, W., & Khan, A. Z. (2024). Factors influencing readiness for artificial intelligence: A systematic literature review. *Data Science and Management*, 8(2), 224–36. <https://doi.org/10.1016/j.dsm.2024.09.005>
- Almufarreh, A., Ahmad, A., Arshad, M., Onn, C. W., & Elechi, R. (2025). Ethical implications of ChatGPT and other large language models in academia. *Frontiers in Artificial Intelligence*, 8(September). <https://doi.org/10.3389/frai.2025.1615761>
- Álvarez-García, E., García-Costa, D., De Waele, I., Marusic, A., & Grimaldo, F. (2026). Expert assignment system based on natural language processing for Marie Skłodowska-Curie actions. *Scientific Reports*, 16(1). <https://doi.org/10.1038/s41598-026-37115-8>
- Baldwin, H., & Borchert, C. (2026, January 21). AI tools are changing academic publishing: How can we adopt them responsibly? *Katina*. <https://doi.org/10.1146/katina-012126-1>
- Bolaños, F., Salatino, A., Osborne, F., & Motta, E. (2024). Artificial intelligence for literature reviews: Opportunities and challenges. *Artificial Intelligence Review*, 57(10). <https://doi.org/10.1007/s10462-024-10902-3>
- Brainard, J. (2023, February 22). As scientists explore AI-written text, journals hammer out policies. *Science*. <https://www.science.org/content/article/scientists-explore-ai-written-text-journals-hammer-policies>
- Brainard, J. (2025). Far more authors use AI to write science papers than admit it, publisher reports. *AAAS Articles DO Group*, 389(6766). <https://doi.org/10.1126/science.z87syeh>
- Cao, C., Sang, J., Arora, R., Chen, D., Kloosterman, R., Cecere, M., Gorla, J., Saleh, R., Drennan, I., Teja, B., Fehlings, M., Ronksley, P., Leung, A. A., Weisz, D., Ware, H., Whelan, M., Emerson, D. B., Arora, R., & Bobrovitz, N. (2025). Development of prompt templates for large language model-driven screening in systematic reviews. *Annals of Internal Medicine*, 178(3). <https://doi.org/10.7326/annals-24-02189>
- Casper, S., Krueger, D., & Hadfield-Menell, D. (2025). *Pitfalls of evidence-based AI policy*. arXiv. <https://arxiv.org/abs/2502.09618>
- Catharina, A., Cobey, K. D., & Moher, D. (2024). Research integrity definitions and challenges. *Journal of Clinical Epidemiology*, 171(111367). <https://doi.org/10.1016/j.jclinepi.2024.111367>
- Clark, D., Nicholas, D., Swigon, M., Abrizah, A., Rodríguez-Bravo, B., Revez, J., Herman, E., Xu, J., &

- Watkinson, A. (2024). Authors, wordsmiths and ghostwriters: Early career researchers' responses to artificial intelligence. *Learned Publishing*, 38(1). <https://doi.org/10.1002/leap.1652>
- Committee on Publication Ethics. (2025, August 26). Emerging AI dilemmas in scholarly publishing. *COPE Forum*. <https://publicationethics.org/topic-discussions/emerging-ai-dilemmas-scholarly-publishing>
- Data Conversion Laboratory Inc. (2026). Audits, analysis, and insight into your content library. *DCL*. <https://www.dataconversionlaboratory.com/content-clarity>
- de Leon, J., de Leon-Martinez, S., Artés-Rodríguez, A., Baca-García, E., & De las Cuevas, C. (2025). Reflections on the potential and risks of AI for scientific article writing after the AI endorsement by some scientific publishers: Focusing on Scopus AI. *Actas Españolas de Psiquiatría*, 53(2), 433–442. <https://doi.org/10.62641/aep.v53i2.1849>
- Dragos, K. (2025). A review of the h-index in the era of generative artificial intelligence. In *Proceedings of the 7th International Workshop on Explainable Artificial Intelligence in Civil Engineering*. Hamburg University of Technology. <https://smarsly.wordpress.com/wp-content/uploads/2025/06/dragos2025c.pdf>
- Engelhardt, M. (2025, September 16). Academic publishing in the age of AI. *ScienceOpen*. <https://blog.scienceopen.com/2025/09/academic-publishing-in-the-age-of-ai/>
- Eren, M. E., & Perez, D. M. (2025, November 14). *Rethinking science in the age of artificial intelligence*. arXiv. <https://arxiv.org/pdf/2511.10524>
- European Association of Science Editors. (2025, February 13). Recommendations on the use of AI in scholarly communication. *EASE*. <https://ease.org.uk/communities/peer-review-committee/peer-review-toolkit/recommendations-on-the-use-of-ai-in-scholarly-communication/>
- Evanko, D. S., & Di Natale, M. (2025, August 25). Quantifying and assessing the use of generative AI by authors and reviewers in the cancer research field. *Peer Review Congress*. <https://peerreviewcongress.org/abstract/quantifying-and-assessing-the-use-of-generative-ai-by-authors-and-reviewers-in-the-cancer-research-field/>
- Field, S. M., Wagenmakers, E.-J., Kiers, H. A. L., Hoekstra, R., Ernst, A. F., & van Ravenzwaaij, D. (2020). The effect of preregistration on trust in empirical research findings: Results of a registered report. *Royal Society Open Science*, 7(4), 181351. <https://doi.org/10.1098/rsos.181351>
- Fleming, E., Noel-Storr, A., Macura, B., Gartlehner, G., Thomas, J., Meerpohl, J. J., Jordan, Z., Minx, J., Eisele-Metzger, A., Hamel, C., Jemioło, P., Porritt, K., & Grainger, M. (2025). Position statement on artificial intelligence (AI) use in evidence synthesis across Cochrane, the Campbell Collaboration, JBI, and the Collaboration for Environmental Evidence 2025. *Campbell Systematic Reviews*, 21(4). <https://doi.org/10.1002/cl2.70074>

- Glynn, A. (2025). Guarding against artificial intelligence—hallucinated citations: The case for full-text reference deposit. *European Science Editing*, 51(51). <https://doi.org/10.3897/ese.2025.e153973>
- Haan, S. (2025). *SemanticCite: Citation verification with AI-powered full-text analysis and evidence-based reasoning*. arXiv. <https://arxiv.org/abs/2511.16198>
- Hill, Z., & Marshall, B. (2026, February 19). When nonprofit leaders should think like creatives. *Stanford Social Innovation Review*. <https://ssir.org/articles/entry/nonprofit-leadership-creative-industries>
- Khalifa, M., & Albadawy, M. (2024). Using artificial intelligence in academic writing and research: An essential productivity tool. *Computer Methods and Programs in Biomedicine Update*, 5(1), 100145. <https://doi.org/10.1016/j.cmpbup.2024.100145>
- Kibuacha, F. (2026, February 17). AI in research: Design and problem definition. *GeoPoll*. <https://www.geopoll.com/blog/ai-research-design/>
- King, H. (2026). AI-powered publishing use cases. *Coda*. <https://coda.io/@helen-king/ai-powered-publishing-use-cases>
- Kiss, R. (2025, May 26). Generative AI in academic publishing: Tools and strategies from Elsevier, Springer Nature and Wiley. *PROMPTREVOLUTION*. <https://promptrevolution.poltextlab.com/generative-ai-in-academic-publishing-tools-and-strategies-from-elsevier-springer-nature-and-wiley/> Archive link: <https://web.archive.org/web/20260308231855/https://promptrevolution.poltextlab.com/generative-ai-in-academic-publishing-tools-and-strategies-from-elsevier-springer-nature-and-wiley/>
- Klontzas, M. E., Groot Lipman, K. B. W., D' Antonoli, T. A., Andreychenko, A., Cuocolo, R., Dietzel, M., Gitto, S., Huisman, H., Santhino, J., Vernuccio, F., Visser, J. J., & Huisman, M. (2025). ESR essentials: Common performance metrics in AI—Practice recommendations by the European Society of Medical Imaging Informatics. *European Radiology*, 36. <https://doi.org/10.1007/s00330-025-11890-w>
- Kumar, A. (2026, February 18). Rethinking academic publishing in the age of AI. *Medium*. <https://medium.com/@sreearun/rethinking-academic-publishing-in-the-age-of-ai-04e83d5c030a>
- Lazer, D., & Ognyanova, K. (2024). The future of computational social science. In J. M. Box-Steffensmeier, D. P. Christenson, & V. Sinclair-Chapman (Eds.), *Oxford handbook of engaged methodological pluralism in political science*. Oxford University Press. <https://doi.org/10.1093/oxfordhb/9780192868282.013.50>
- Lazer, D., Pentland, L., Adamic, S., Aral, A.-L., Barabasi, D., Brewer, N., Christakis, Contractor, N., Fowler, J., Gutmann, M., Jebara, T., King, G., Macy, M., Roy, D., & Van Alstyne, M. (2009). Computational social science. *Science*, 323(5915), 721–23.

<https://doi.org/10.1126/science.1167742>

Mayers, S. (2025, August 21). How AI is transforming peer review. *ScienceOpen Blog*.
<https://blog.scienceopen.com/2025/08/how-ai-is-transforming-peer-review/>

Mollaki, V. (2024). Death of a reviewer or death of peer review integrity? The challenges of using AI tools in peer reviewing and the need to go beyond publishing policies. *Research Ethics*, 20(2), 239–250. <https://doi.org/10.1177/17470161231224552>

Nicholas, D., Abrizah, A., Clark, D., Rodríguez-Bravo, B., Revez, J., Herman, E., Świgoń, M., Xu, J., & Watkinson, A. (2025). Early career researchers open-up on citations in respect to reputation, trust, ethics, AI and much more. *Learned Publishing*, 38(3). <https://doi.org/10.1002/leap.2015>

Nicholas, D., Herman, E., Clark, D., Abrizah, A., Revez, J., Rodríguez-Bravo, B., Świgoń, M., Xu, J., & Watkinson, A. (2025). Integrity and misconduct: Where does artificial intelligence lead? *Learned Publishing*, 38(3). <https://doi.org/10.1002/leap.2013>

O'Neill, T., McNeese, N., Barron, A., & Schelble, B. (2020). Human-autonomy teaming: A review and analysis of the empirical literature. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 64(5), 00187208209608 <https://doi.org/10.1177/0018720820960865>

Octopus. (2026). Octopus: Aims and priorities. *Octopus.ac*. <https://www.octopus.ac/octopus-aims>

Resnik, D. B., & Hosseini, M. (2025). Disclosing artificial intelligence use in scientific research and publication: When should disclosure be mandatory, optional, or unnecessary? *Accountability in Research*, 33(2), 1–13. <https://doi.org/10.1080/08989621.2025.2481949>

Reviewer Credits. (2024, August 19). Digital tools & AI tools for journal editors. *Reviewer Credits*.
<https://www.reviewercredits.com/digital-and-ai-tools-for-journal-editors/>

Rogers, A., Richard, B., Borchert, C., Peck, L., & Holt, S. (2025, August 19). Guest post—beyond open access, part 1: Make academic content truly accessible for all. *The Scholarly Kitchen*.
<https://scholarlykitchen.sspnet.org/2025/08/19/guest-post-beyond-open-access-part-1-make-academic-content-truly-accessible-for-all/>

Scopus (2026). Scopus AI website, June 21 2026, <https://www.elsevier.com/products/scopus/scopus-ai>

Simis, L. (2025). AI in scholarly publishing: Expert predictions for 2025. *Hum.works*.
<https://blog.hum.works/posts/ai-predictions-for-2025>

Springer-Nature. (2023). Springer Nature introduces AI-powered scientific writing assistant. *Springernature.com*. <https://group.springernature.com/gp/group/media/press-releases/archive-2023/ai-powered-scientific-writing-assitant-launched/26176230>

Springer-Nature. (2025). Living and static reference works. *Springer Nature Support*.

<https://support.springernature.com/en/support/solutions/articles/6000233379-living-and-static-reference-works>

Springer-Nature (2025b). What is Rubriq on Research Square? Tue, 23 Dec, 2025.

<https://support.springernature.com/en/support/solutions/articles/6000280903-what-is-rubriq-on-research-square->

Stokel-Walker, C. (2023). ChatGPT listed as author on research papers: Many scientists disapprove.

Nature, 613(7945). <https://doi.org/10.1038/d41586-023-00107-z>

Wiley. (2025). ExplainAItions 2025: The evolution of AI in research. *Wiley*.

<https://www.wiley.com/content/dam/wiley-com/en/pdfs/about/wiley-explanaitions-2025-the-evolution-of-ai-in-research.pdf>

Willinsky, J., & Pimentel, D. (2024). The publication facts label: A public and professional guide for research articles. *Learned Publishing*, 37(2), 139–46. <https://doi.org/10.1002/leap.1599>

Wong, J. (2024, October 31). Importance of citations in academic writing. *Jenni.ai*.

<https://jenni.ai/blog/importance-of-citations-academic-writing>

Yan, L., Sha, L., Zhao, L., Li, Y., Martinez-Maldonado, R., Chen, G., Li, X., Jin, Y., & Gašević, D. (2023).

Practical and ethical challenges of large language models in education: A systematic scoping review. *ArXiv (Cornell University)*, 55(1). <https://doi.org/10.1111/bjet.13370>

Zhou, H. (2025, April 29). AI strategy, governance, and monetization in scholarly publishing: Lessons from industry front-runners. *The Scholarly Kitchen*.

<https://scholarlykitchen.sspnet.org/2025/04/29/ai-strategy-governance-and-monetization-in-scholarly-publishing-lessons-from-industry-front-runners/>

