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REVIEW ARTICLE

Artificial Intelligence in Scholarly Publishing: Enhancing Editorial Efficiency While Preserving Human Expertise

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Abstract
Use of artificial Intelligence (AI) is increasing significantly in scholarly publishing. It can potentially enhance editorial workflows and reduce the burden on reviewers. AI applications, like plagiarism detection, formatting checks, and reviewer assignment, can improve efficiency and transparency during initial manuscript processing stages. However, the peer review process extends beyond mere technical tasks. It encompasses critical evaluation that requires human expertise, contextual understanding, and ethical consideration. This review highlights the constraints of using AI in peer review while examining both present and future uses of AI in editorial activities. A fair framework has been created, and AI can assist with editorial tasks rather than replace human reviewers. Peer review's integrity, legitimacy, and constructive character depend on human judgment. This review also emphasises the mounting issues facing the traditional peer review system, such as rising submission numbers, reviewer exhaustion, and delays in decision-making. To ensure that scientific publishing upholds its exacting standards, this narrative emphasises the importance of keeping human evaluation at the centre of the review process by addressing both advantages and disadvantages of integrating AI.

Keywords: Artificial Intelligence; Peer Review; Editorial Policies; Scholarly Journals; Research Integrity; Scientific Misconduct

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Key Highlights

- AI has the potential to streamline editorial workflows
- Requires human expertise, contextual understanding, and ethical discernment.
- A balanced framework in which AI supports editorial processes without replacing human intervention

Introduction

Peer review is essential to scientific publishing, ensuring that research disseminated to the academic community is accurate and meaningful [1]. Despite its importance, the editorial and publishing system faces several challenges of growing submission volumes, reviewer fatigue, delays in decision-making, and concerns over inconsistency and bias [2]. These challenges have prompted discussion of their technological solutions, including Artificial Intelligence (AI), to improve the efficiency and reliability of academic publishing.

AI has already been used in a few related publishing domains, such as plagiarism detection, grammar checking, and image integrity screening [3]. A more ambitious application involves using AI-generated peer review reports, which is still under discussion [4]. While these uses of AI in the peer review process may offer short-term gains, in the near future, they will complicate questions about the role of human judgment in evaluating scientific knowledge [5].

This review synthesises evidence on opportunities and limitations of AI in peer review, arguing for a clear boundary, stating that "AI can support editorial efficiency, but critical appraisal must remain human-led."

Opportunities for Editorial Efficiency

Increased submission volumes and ongoing peer review process delays put pressure on scientific publishing to operate smoothly. These difficulties draw attention to areas where editorial operations can be improved. Across fields, the time to first decision varies significantly. Typical public health and medicine duration is roughly 8–9 weeks, while the average duration in non-medical specialties is approximately 16–18 weeks [6]. When several rounds of revision are considered, the review process can take up to 12–14 weeks in the medical sciences and frequently more than 25 weeks in non-medical professions [7]. Such extended timescales can irritate authors and delay the spread of knowledge.

Desk rejection is a common gatekeeping technique editorial offices use to control the reviewers' workload. Desk rejection rates in a select few journals range from 30% to over 50%, with an average of 40% [8]. Depending on journal scope and editorial criteria, reported desk rejection rates vary significantly across fields, ranging from as low as 7% to as high as 88% [8].

Some publications have adopted effective screening procedures despite these delays. For instance, one medical journal in the psychiatry specialty had a median desk rejection time of three days, meaning that more than half of submissions were either desk-rejected or progressed to peer review within the first week [9]. This shows that prompt early decisions can be made, saving reviewer capacity and reducing needless waiting times for authors.

When taken as a whole, these statistics highlight obstacles and chances to increase editorial productivity. Journals can improve author experience overall, reduce delays, and better utilise reviewer resources by integrating innovations like AI-assisted triage with strong early screening procedures. The opportunities to enhance scientific scholarship can be further discussed under headings (Table 1).

Table 1. Opportunities for AI in Editorial Efficiency

Editorial Task	Current Challenge	AI Application	Potential Impact	Status
Plagiarism detection	Time-consuming manual checks	Similarity check software (iThenticate, Turnitin)	Faster detection, reduced reviewer burden	Currently Implemented
Formatting and language editing	Inconsistent submissions, burden on reviewers	Grammarly, Writefull, automated formatting tools	Improved readability, consistency	Currently Implemented
Statistical validation	Misreported or inappropriate analyses	Automated stat checkers, algorithm-based flagging	Early error detection, fewer flawed reviews	Emerging Applications
Image/data integrity	Fabrication/manipulation is challenging to spot manually	AI image forensics, anomaly detection	Reduced misconduct, stronger reliability	Emerging Applications
Reviewer selection	Time-intensive search, mismatch of expertise	AI reviewer matching algorithms (Publons, Expert Finder)	More efficient, expertise-aligned assignment	Currently Implemented

Plagiarism Detection

AI-based similarity detection tools such as iThenticate and Turnitin have become standard in many journals [10]. These tools rapidly flag overlapping text, duplicate publications, and suspected self-plagiarism, enabling editors to make informed decisions before sending manuscripts to review. This has significantly reduced the burden on reviewers, who otherwise would spend time identifying such issues.

Formatting and Language Editing

AI-driven writing assistants such as Grammarly and Writefull can identify grammar errors, awkward phrasing, and formatting inconsistencies. They are particularly valuable for authors writing in a second language and for journals that receive submissions with varied adherence to style guidelines. Automated pre-screening ensures that reviewers focus on content rather than superficial errors [11].

Statistical Validation

Emerging AI tools can evaluate whether statistical methods are appropriate for the data type, identify mismatches between reported results and figures, and detect common methodological flaws [12]. automated software can flag missing sample size justifications, inconsistencies between trial registration and reporting, or incorrect p-value interpretations. These applications reduce technical errors before peer reviewers engage with the manuscript.

Image and Data Integrity

AI algorithms are increasingly sophisticated at detecting image duplication, inappropriate manipulation, or statistical anomalies that may suggest fabrication [13]. Editorial offices' Early application of these tools strengthens the quality assurance process before manuscripts undergo critical evaluation.

Reviewer Selection

AI platforms such as Publons Reviewer Locator and Elsevier's Expert Finder analyse publication databases to recommend appropriate reviewers [14]. These tools can match reviewer expertise with manuscript content more efficiently than manual searches, reducing delays and minimising conflicts of interest.

AI tools can be trained to detect potential reviewer biases, such as an unusual number of self-citations or systematic preference for specific authors or institutions [15]. For example, algorithms may flag when a reviewer disproportionately recommends their work, but the final judgment about whether this constitutes undue bias still requires human editorial oversight.

Limits to Critical Appraisal

While AI excels at mechanical checks, several essential elements remain outside its scope (Table 2).

Table 2. Limits of AI in Critical Appraisal

Domain	Why AI Falls Short	Human Reviewer Contribution
Conceptual novelty	AI relies on past data, struggles with originality	Judges' innovation, context, relevance
Ethical oversight	Cannot interpret nuanced ethical considerations	Ensures compliance with patient/animal/research ethics
Bias handling	May reinforce existing publishing biases	Promotes diversity, fairness, and novel approaches
Constructive feedback	Cannot mentor or suggest nuanced improvements	Provides developmental and collegial feedback
Accountability	No ownership of evaluations or errors	Assumes responsibility, maintains transparency

Conceptual Novelty

AI systems are trained on past literature and patterns, but peer review often involves evaluating novelty, originality, and conceptual significance; dimensions that extend beyond pattern recognition [16]. Human reviewers assess whether a study advances knowledge, addresses a relevant gap, or challenges existing paradigms, something AI cannot reliably judge.

Ethical Oversight

Evaluating whether a study adheres to ethical norms, such as informed consent, animal welfare standards, or responsible data use, requires nuanced human interpretation [17]. AI cannot weigh cultural, contextual, or situational subtleties inherent in ethical judgments.

Bias Handling

AI reflects biases present in its training data [18]. If trained predominantly on established literature, AI tools may undervalue innovative or interdisciplinary research that deviates from conventional patterns [19]. This risks reinforcing conservative publishing practices and marginalising underrepresented voices or novel approaches.

Constructive Feedback

Peer review is not only evaluative but also developmental. Reviewers provide constructive feedback, suggest alternative methods, recommend additional literature, and mentor authors, particularly early-career researchers [20]. AI cannot replicate this collegial, dialogic role that fosters scientific growth.

Accountability

Peer reviewers assume responsibility for their judgments and can be held accountable by editors and authors [21]. AI-generated reviews lack ownership, raising questions about responsibility, liability, and trustworthiness. The opacity of many AI systems ("black-box" algorithms) further complicates accountability in scholarly communication [22].

Balancing AI and Human Roles

A balanced and practical approach positions AI as a supportive tool in the editorial pre-screening phase, rather than replacing human reviewers. Peer-review inefficiencies remain a persistent burden for both editors and reviewers. A significant fraction of submissions, approximately 21%, are desk-rejected before peer review, yet in many cases, these decisions take more than four weeks to be communicated, prolonging delays for authors [8]. Meanwhile, reviewers dedicate substantial time and effort, averaging 11.5 hours per manuscript. This amounts to an estimated 15 million hours annually spent on peer review, a considerable proportion of which is consumed by manuscripts ultimately rejected at later stages [23].

Recent analyses have highlighted that reviewers may demonstrate bias toward articles that cite their work, with approval rates significantly higher when self-citations are included. This reflects an inherent vulnerability of peer review where subjective incentives override objective appraisal, a dimension that current AI-assisted tools could flag for editorial oversight [15].

By delegating routine, automatable tasks to AI, such as checking for formatting inconsistencies, reference style errors, or plagiarism, human reviewers can focus their efforts where they matter most: the critical appraisal of scientific novelty, methodological rigour, ethical standards, and overall contribution to the field. One leading publisher has emphasised that plagiarism detection and related technical assessments are more appropriately considered "a role of editorial assessment, not a peer-review process." This highlights a natural boundary where AI can enhance efficiency while preserving the irreplaceable role of human expertise in scientific judgment [24].

The most pragmatic use of AI in peer review is as a supportive, pre-screening tool within the editorial office rather than replacing human reviewers [25]. Just as plagiarism detection software has become standard practice in nearly all journals, AI can conduct additional technical checks before a manuscript is passed to reviewers. These checks may include formatting compliance, statistical screening, language and clarity checks, image integrity verification, and reviewer selection assistance.

By taking over these repetitive and administrative tasks, AI allows reviewers to focus their expertise on more profound questions: Does this study advance knowledge? Is the methodology rigorous and ethical? Do data support conclusions? This division of labour enhances efficiency, minimises reviewer fatigue, and shortens decision timelines without eroding the integrity of the peer review system.

Equally important, journals should maintain transparency about where and how AI has been used. Authors and reviewers should be informed if AI tools screened their manuscripts or contributed to workflow decisions. Such openness fosters trust in the editorial process and guards against misuse or overreliance on algorithms.

Future Directions

The integration of AI into peer review is still evolving, and future directions must focus on creating a balanced system that leverages efficiency without undermining critical human appraisal. Several key areas deserve attention (Figure 1).

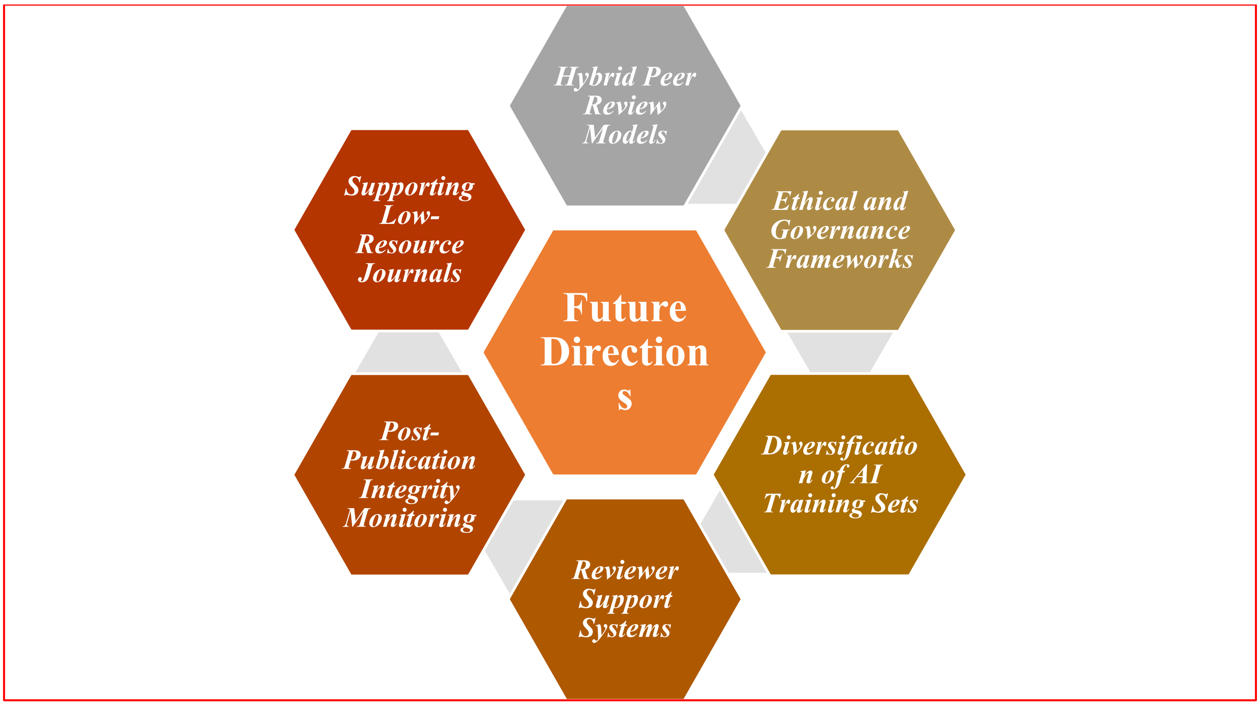

Figure 1. Future Directions in the Use of AI for Peer Review of Scientific Articles

Hybrid Peer Review Models

AI can produce structured "pre-review checklists" summarising technical findings such as similarity scores, statistical anomalies, or image duplication, allowing reviewers to concentrate on higher-level critique. Preliminary reports from ICLR 2024 suggested that AI involvement may influence review outcomes: at ICLR 2024, 15.8% of reviews were AI-assisted, and these reviews gave higher scores in 53.4% of cases, resulting in approximately a 4.9 percentage point increase in acceptance probability for manuscripts using AI assistance [26]. Such data remain preliminary and require validation across multiple venues before generalisation; however, such findings highlight both potential and risks of integrating AI into evaluative processes.

Ethical and Governance Frameworks

Journals are increasingly recognising the need for AI policies. According to publisher policy reviews conducted in 2023, among the top 100 journals, 70% had formal policies on using generative AI, with nearly 95% prohibiting AI as an author. However, only 43–45% mandated disclosure of AI use, and policy details varied widely across publishers [24]. Several analyses of publisher guidelines indicate that harmonised, transparent guidelines are critical to ensure consistency and protect research integrity.

Diversification of AI Training Sets

Most current AI tools are disproportionately trained on English-language, high-impact literature, which risks amplifying systemic biases. A recent survey 2025, (pre-print) suggested that ChatGPT accounted for 77% of AI use in academic writing, with 51% applied to readability improvement and 22% to grammar correction, particularly among non-native English authors [28]. Findings are preliminary and not yet peer-reviewed; however, they suggest that expanding training datasets to incorporate multilingual and regionally diverse scholarship will help AI tools serve the global scientific community more equitably.

Reviewer Support Systems

Beyond technical screening, AI can augment reviewer capacity by curating relevant resources, providing literature summaries, and flagging methodological checklists. Such systems could strengthen review depth while leaving judgment of novelty, rigour, and significance firmly in human hands.

Post-Publication Integrity Monitoring

AI also offers opportunities for ongoing oversight after publication. Automated tools can detect image duplication, identify contradictory datasets, and flag undeclared conflicts of interest, providing an additional safeguard when combined with traditional post-publication peer review. This ongoing surveillance could significantly improve the reliability of the scientific record.

Supporting Low-Resource Journals

In regions or journals with limited editorial infrastructure, AI can serve as a technical ally, screening for plagiarism, formatting issues, or reference errors. Nevertheless, human oversight remains essential to avoid over-reliance on automated systems and ensure editorial decisions reflect scholarly merit rather than algorithmic gatekeeping.

Taken together, these future directions emphasise that AI should serve as a tool to support, not replace, human expertise. The peer review ecosystem can evolve toward greater efficiency, equity, and integrity by adopting hybrid models, building governance frameworks, addressing systemic biases, and extending support to low-resource journals.

Conclusion

Several chances exist to improve editorial efficiency through integrating AI in peer review, especially in increasing submission quantities and reducing delays. The workload for human reviewers can be reduced by using AI systems to automate various tasks, including plagiarism detection and document formatting. Notwithstanding these developments, human expertise, context, and ethical judgment are still required for critical research evaluation, highlighting AI's limitations in completely replacing human reviewers. The review promotes a well-rounded strategy in which AI aids editorial procedures, enabling quicker judgments while maintaining the integrity and legitimacy of scientific publishing. In the end, maintaining the strict standards for disseminating high-quality research requires keeping human interaction at the centre of peer review.

Statements and Declarations

Ethics Approval and Consent to Participate: Not applicable. This manuscript is a narrative review and did not involve human participants or animals

Consent for Publication

Not applicable.

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The author(s) declare no competing interests.

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Author's contribution

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Use of AI tools

The authors have used Grammarly for English editing and improving the manuscript's readability, but have rechecked its final contents and take full responsibility.

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