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To Use or Not to Use AI as Referees in Scientific Journals? Proposal for a More Efficient Model

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Abstract: The peer review process plays a critical role in ensuring the quality, reliability and validity of scientific publications. However, traditional peer review faces increasing challenges, including prolonged review times, reviewer fatigue, and inherent biases, which impact its efficiency and objectivity. Recent advancements in artificial intelligence (AI), particularly in natural language processing (NLP) and large language models (LLMs), offer promising solutions for automating aspects of peer review. This study explores the feasibility of AI-driven peer review, assessing its potential benefits and limitations. AI tools can expedite manuscript screening, detect plagiarism, verify statistical accuracy, and ensure adherence to journal guidelines, reducing the burden on human reiewers and accelerating publication timelines. However, concerns persist regarding AI's lack of critical judgment, potential algorithmic biases, and transparency issues. A hybrid AI-human peer review model is proposed, where AI handles initial screening and technical checks while human reviewers focus on intellectual and contextual evaluations. This integrated approach could enhance the efficiency and fairness of the peer-review process while maintaining scientific rigor. The study underscores the need for ethical frameworks transparency measures, and continuous improvements to AI systems to ensure responsible AI integration in academic publishing.

Resumen: El proceso de revisión por pares desempeña un papel fundamental a la hora de garantizar la calidad, la fiabilidad y la validez de las publicaciones científicas. Sin embargo, la revisión por pares tradicional se enfrenta a desafíos cada vez mayores, incluidos tiempos de revisión prolongados, fatiga del revisor y sesgos inherentes, que afectan su eficiencia y objetividad. Los avances recientes en inteligencia artificial (IA), particularmente en el procesamiento del lenguaje natural (NLP) y los grandes modelos de lenguaje (LLM), ofrecen soluciones prometedoras para automatizar aspectos de la revisión por pares. Este estudio explora la viabilidad de la revisión por pares impulsada por IA, evaluando sus posibles beneficios y limitaciones. Las herramientas de IA pueden acelerar la selección de manuscritos, detectar plagios, verificar la precisión estadística y garantizar el cumplimiento de las directrices de las revistas, lo que reduce la carga de los trabajadores humanos y acelera los plazos de publicación. Sin embargo, persisten las preocupaciones sobre la falta de juicio crítico de la IA, los posibles sesgos algorítmicos y los problemas de transparencia. Se propone un modelo híbrido de revisión por pares entre IA y humanos, en el que la IA se encarga de la selección inicial y las comprobaciones técnicas, mientras que los revisores humanos se centran en las evaluaciones intelectuales y contextuales. Este enfoque integrado podría mejorar la

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eficiencia y la equidad del proceso de revisión por pares, manteniendo al mismo tiempo el rigor científico. El estudio subraya la necesidad de marcos éticos, medidas de transparencia y mejoras continuas en los sistemas de IA para garantizar una integración responsable de la IA en las publicaciones académicas.

Keywords: Peer review; Artificial intelligence; Large language models; Academic publishing; AI ethics; Hybrid peer review model.
Palabras clave: Revisión por pares; Inteligencia artificial; Grandes modelos de lenguaje; Publicaciones académicas; Ética de la IA; Modelo híbrido de revisión por pares.

1 Introduction

Peer review is the cornerstone of scientific publishing, ensuring the quality, reliability, and validity of research before dissemination. It serves as a mechanism for verifying methodologies, analyzing results, and filtering out low-quality studies. However, the traditional peer-review process has long been criticized for its inefficiencies, including lengthy review times, increasing reviewer workload, and biases that may affect editorial decisions. These issues have raised concerns about the sustainability of the peer-review model in an era of exponential scientific output and increasing journal submissions [1]. A study conducted by Tennant et al. [2] found that the average time from manuscript submission to publication varies between 3 and 6 months, with more complex reviews extending beyond 12 months. Additionally, the burden on reviewers has been increasing, as many are required to review manuscripts without adequate incentives, leading to delays, inconsistencies, and reviewer fatigue [3]. Furthermore, biases in peer review—whether based on author reputation, institutional affiliation, or gender disparities—raise concerns regarding fairness and objectivity in research evaluation [4]. In response to these issues, artificial intelligence (AI) has emerged as a potentially transformative tool for scientific publishing. The application of AI in peer review is gaining traction, particularly with advancements in natural language processing (NLP), generative models, and automated decision-making algorithms [5]. AI-based tools can already assist in tasks such as plagiarism detection, statistical verification, and readability assessment. Some AI models have also been trained to provide preliminary evaluations of research quality, identifying weak methodologies and detecting potential errors before human intervention [6]. A crucial question arises: Can AI replace human referees in scientific journals? While AI has the potential to expedite reviews and enhance objectivity, it also presents ethical, technical, and transparency-related challenges [7]. The aim of this article is to explore the feasibility of AI in peer review, discuss its advantages and limitations, and evaluate its broader impact on the scientific community.

2 The problem with peer review and the emerging role of AI

Despite being the gold standard for maintaining research integrity, the peer-review system is plagued with systemic inefficiencies that hinder the efficiency, objectivity, and speed of academic publishing. While peer review serves as a quality control mechanism, ensuring that published research meets scientific standards, its limitations have become increasingly evident in the face of the rising volume of scientific output [8].

One of the most pressing issues in the current peer-review system is lengthy review times. Studies indicate that the average review time for high-impact journals ranges between 90 to 180 days, with some extending beyond a year [9]. The rapid expansion of research, especially in areas such as biomedical sciences and artificial intelligence, has further strained the system, leading to bottlenecks that delay the dissemination of critical discoveries. The COVID-19 pandemic underscored this issue, prompting the rise of preprint servers as a means of bypassing traditional peer-review delays [10].

Additionally, reviewer workload has become increasingly unsustainable. A growing number of researchers are declining review requests due to the lack of proper incentives and increasing time constraints [11]. Journals often struggle to find qualified reviewers, which leads to delays and, in some cases, rushed or superficial evaluations. This problem, known as peer-review fatigue, negatively impacts the overall quality of published research [12].

2.1 Bias and inconsistencies in peer review

Although the peer-review system is designed to be objective, multiple studies have highlighted its susceptibility to bias, including: i) confirmation bias: Reviewers are more likely to accept research that aligns with existing dominant theories, potentially discouraging innovative or disruptive findings [13], ii) institutional and author bias: Manuscripts from renowned universities or well-known researchers tend to receive preferential treatment, independent of their scientific quality [14], and iii) gender and geographical bias: Studies indicate that researchers from Western institutions and male authors tend to have higher acceptance rates, raising concerns about inequality in scientific publishing [15].

Such inconsistencies and subjective influences significantly affect the fairness and credibility of peer review. Given these limitations, researchers and publishers have begun to explore artificial intelligence (AI) as a potential solution to improve the efficiency, objectivity, and scalability of the process [16].

2.2 The rise of AI in peer review

The recent advancements in AI-driven language models and machine learning have positioned AI as a viable tool for automating aspects of peer review. Large-scale Transformer architectures, such as ChatGPT [17], DeepSeek [18], Gemini [19], and Qwen [20], have demonstrated the ability to analyze and synthesize complex scientific texts, provid ing rapid evaluations of manuscripts with increasing accuracy [21]. AI-based peer review can assist with: i) manuscript readability and coherence assessments, ii) detection of sta tistical inconsistencies and methodological flaws, iii) plagiarism and citation analysis, and iv) checking adherence to journal formatting guidelines. Several AI-driven peer review tools, such as Elicit [22] and Scite [23], are already being utilized to analyze citation networks, detect argument weaknesses, and evaluate biases in research. These AI systems complement human reviewers by streamlining the assessment process, reducing errors, and enhancing objectivity.

2.3 Towards a hybrid AI-human review system

While fully replacing human reviewers with AI remains controversial, a hybrid approach that integrates AI and human expertise appears to be the most promising solution. In such a model: i) AI performs an initial manuscript screening, identifying fundamental errors, plagiarism, and inconsistencies, ii) human reviewers focus on deeper scientific aspects, evaluating originality, experimental design, and impact, and iii) AI assists in crossreferencing research findings, ensuring alignment with existing literature and journal requirements.

This AI-human synergy could optimize the peer-review process, significantly reducing review times while preserving scientific rigor and ensuring high-quality assessments [24]. As AI models continue to evolve, journals and publishers must establish ethical guidelines to ensure transparency, fairness, and responsible AI use in scientific evaluations. Rather than replacing human judgment, AI should serve as a tool to support and enhance the peer-review process, making it faster, fairer, and more efficient [25].

3 Benefits and limitations of AI in peer review

AI has the potential to transform peer review by addressing key inefficiencies such as slow evaluation times, inconsistencies in reviews, and reviewer fatigue. While AI offers significant advantages in speed, consistency, and bias reduction, its limitations in critical thinking, contextual judgment, and transparency pose challenges to its widespread adoption in academic publishing.

3.1 Advantages of AI in peer review

The implementation of AI in scientific peer review could revolutionize the way manuscripts are assessed. Below are some of the major advantages of AI-assisted peer review:

1. Speed and efficiency. Traditional peer review can take months or even years, delaying the publication of potentially groundbreaking research [26]. AI-powered models can analyze hundreds of manuscripts in hours, flagging errors, evaluating statistical
2. Reduction of human bias. Human reviewers, despite their expertise, are prone to cognitive biases. Studies have shown that author reputation, institutional affiliation, and gender bias can significantly influence acceptance rates in peer review [28]. AI, when properly trained, can eliminate these biases by focusing purely on content quality, without being affected by preconceived notions or conflicts of interest [29]. However, the extent to which AI can truly be "bias-free" depends on the data used for training the models.
3. Improved detection of errors and plagiarism. Plagiarism and research misconduct remain persistent problems in academic publishing [30]. AI tools, such as Turnitin, Ouriginal and iThenticate, are already widely used for detecting text similarities, but more advanced AI systems can now analyze data integrity, image manipulation, and citation accuracy [31]. These systems can identify inconsistencies in datasets, flag sta tistical errors, and even detect potential scientific fraud before a manuscript proceeds further in the review process.
4. Consistent evaluation criteria. Unlike human reviewers, who may apply varied subjective standards, AI operates with predefined and replicable criteria. This ensures that all manuscripts are evaluated fairly, without inconsistencies due to reviewer experience levels, workload, or fatigue [32]. The use of AI can also standardize formatting checks and enforce journal guidelines, ensuring manuscripts meet submission requirements before being assigned to human reviewers.

3.2. Challenges and limitations

Despite its numerous benefits, AI-based peer review presents several limitations and challenges that must be carefully addressed before widespread implementation:

1. Lack of critical judgment and creativity. AI can efficiently identify patterns and errors, but it lacks the ability to interpret the broader impact and significance of research. Peer review is not only about checking for errors but also evaluating the novelty, scientific contribution, and theoretical implications of a study [33]. AI struggles to assess the originality of ideas, and understanding the social, ethical, and interdisciplinary impact of research remains beyond its current capabilities.
2. Potential algorithmic biases. Although AI is often seen as an unbiased evaluator, AI models can inherit biases from the datasets they are trained on. If historical peer-review data contain institutional, regional, or gender biases, AI might replicate and even amplify these biases [34]. Transparency in how AI systems are trained and what datasets are used is crucial to ensuring fairness in automated peer review.
3. Lack of transparency and accountability. Many AI models function as "black boxes", meaning their decision-making processes are not fully interpretable [35]. This creates challenges for editors and researchers who need to understand why a manuscript was flagged or rejected by AI. Ensuring explainability in AI-driven peer review will be essential to building trust within the academic community.
4. Resistance from the scientific community. Many researchers and journal editors remain skeptical about integrating AI into peer review, citing concerns about automation replacing human judgment and even individual human expression and creativity [36]. Editors may hesitate to rely on AI for manuscript acceptance decisions, particularly in highly specialized fields where nuanced human expertise is crucial, because the algorithms are not neutral, but are opinions created in code by the AI, trained with the scientific information provided to it. Addressing these concerns through education, transparency, and hybrid AI-human workflows will be critical for adoption. The proposal of the hybrid model assumes a clear division between the technical tasks of AI, so that AI is a tool for review, and the human intellectual evaluation o supervision, necessarily robust and aware of the ethical and technical limitations of AI.

3.3 AI as a support system or a replacement?

3.3.1 Proposed AI-human hybrid workflow

Rather than completely replacing human referees, AI is best positioned as an enhancement tool, assisting rather than eliminating human judgment. While AI has demonstrated remarkable efficiency in handling large-scale textual analysis, detecting inconsistencies, and ensuring compliance with editorial guidelines, it still lacks the cognitive depth and contextual awareness necessary for assessing scientific novelty, research significance, and ethical considerations [37]. The ideal solution is a hybrid AI-human peer review model that leverages AI for efficiency, standardization, and error detection, while retaining human oversight for intellectual evaluation and contextual interpretation. This collaborative approach can accelerate publication timelines, improve review accuracy, and enhance transparency in decision-making.

Figure 1 shows the AI-human hybrid peer review workflow of our proposal; which outlines the integration of AI and human expertise in the manuscript review process, ensuring efficiency, objectivity, and quality in scientific publishing.

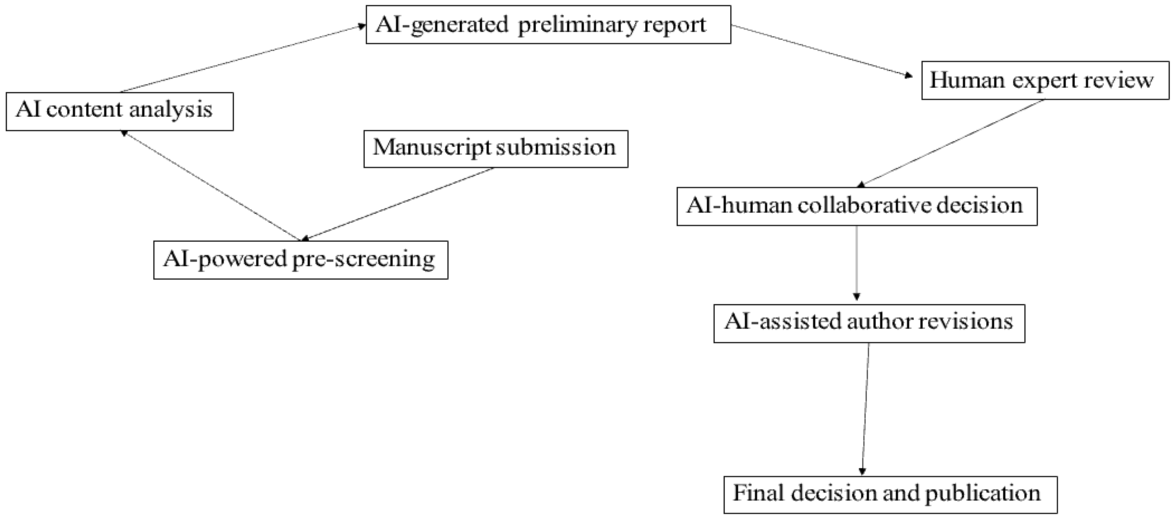

Figure 1. AI-Human hybrid peer review workflow in our proposal.

In fact, a structured AI-human peer review model could streamline the review process by assigning distinct roles to AI systems and human referees being structured in several phases:

- Phase 1: AI-driven initial screening. AI conducts preliminary checks, which include:
  - Plagiarism detection: AI-based similarity detection tools (e.g., iThenticate, Turnitin, and CrossRef Similarity Check) scan manuscripts for text over laps and potential plagiarism [38].
  - Formatting compliance: AI verifies manuscript structure, journal formatting, reference accuracy, and adherence to ethical guidelines [39].
  - Statistical verification: AI flags inconsistencies in data reporting, statistical significance, and experimental reproducibility using automated tools like Statcheck and AI-

driven meta-analysis software [40].

    - Technical clarity assessment: AI evaluates sentence structure, grammar, and readability, ensuring that the manuscript meets basic language standards before human review [41].

- Phase 2: AI-assisted review report. AI generates a preliminary evaluation report highlighting structural strengths, weaknesses, and flagged issues. Editors and reviewers receive an AI-generated summary to prioritize critical review areas [42].
- Phase 3: Humana reviewer evaluation. After AI processing, expert reviewers focus on aspects requiring scientific interpretation [43], including:
    - Evaluating research significance, novelty, and originality.
    - Assessing conceptual depth, argumentation, and hypothesis soundness.
    - Interpreting methodology validity beyond statistical calculations.
    - Reviewing potential ethical concerns in experimental desing and subject handling.
- Phase 4: AI-human decision integration [44]:
    - AI models assist in cross-referencing reviewer feedback to identify contradictions or inconsistencies in reviewer comments.
    - AI ranks reviews based on coherence, level of agreement, and depth of critique, helping editors make more data-driven decisions.
    - Editors combine AI-assisted insights with human evaluations to finalize decisions (Accept, Revise, Reject).
- Phase 5: AI-assited author revisions [45]:
    - AI suggests grammar, structure, and reference improvements based on re viewer feedback.
    - AI tools assist authors in improving their responses to reviewer comments to facilitate faster resubmission cycles.
- Phase 6: Final editorial decision and publication [46]:
    - Human editors conduct a final quality control check before publication.
    - AI ensures that all formatting, metadata, and citation styles are consistent and compliant.

Table 1 shows a fictitious practical example that allows us to observe the proposal in operation.

3.3.2 Adoption and current implementations of AI-assisted peer review

Several high-profile scientific journals have already begun piloting AI-based peer review systems, with promising results in improving efficiency, accuracy, and reproducibility. For example, Nature and Springer Nature have tested AI-powered editorial workflows to handle preliminary checks before assigning reviewers [47] and MDPI [48] journals have implemented automated AI-based quality checks before assigning human referees, significantly reducing the workload of editorial teams. These findings suggest that AI-assisted peer review systems are becoming increasingly reliable for early-stage assessments, helping journals maintain rigor and efficiency in the publishing process.

Table 1. A fictitious practical example of how the hybrid model works.

<table>
<tr><td colspan="2">Dr. Carmen García submits her manuscript entitled "The impact of nutrition on neuronal plasticity in older adults" to the fictitious journal "Journal of Cognitive Neuroscience" that has implemented the hybrid model.</td></tr>
<tr><th>Phases of the hybrid model</th><th>Actions taken</th></tr>
<tr><td>Phase 1: Initial AI screening

Immediately after Dr. Garcia submits her article through the journal's portal, the AI system is activated.

In less than an hour, the system has completed its analysis.</td><td>1. Plagiarism detection: The AI scans the manuscript and compares it to a vast database of existing publications. It detects an 8% similarity in the "Introduction" section to a previously published review article, but flags it as an acceptable match of standard terminology and not plagiarism.
2. Compliance with the format: The system verifies that the article complies with the journal's guidelines: structure (Abstract, Introduction, Material and Methods, Results, Discussion and Conclusions), citation style (APA 7th ed.) and number of words. The AI points out that two references in the literature do not follow the APA format correctly.
3. Statistical verification: The AI analyzes the "Results" section. She identifies that in Table 2, a p-value of 0.045 is reported, but the analysis of the raw data (which Dr. García uploaded as an annex) suggests that the p-value should be 0.054. He marks it as a "statistical inconsistency".
4. Technical clarity: The language model evaluates the readability of the text, concluding that it has a high clarity, but suggests rephrasing two sentences in the "Discussion" because they are too long and complex.</td></tr>
<tr><td>Phase 2: AI-Assisted Reporting
The section's editor, Dr. Chen, receives a notification. Instead of a simple manuscript, it receives a report from the AI.

This report allows Dr. Chen to decide within minutes that the article has enough merit to move on to peer review, rather than spending hours on an initial review.</td><td>• AI report. It presents a summary that indicates:

o Plagiarism: Minor alert (low similarity).
o Format: Minor alert (2 citation errors).
o Statistic: Critical Alert (discrepancy in p-value in Table 2).
o Clarity: Minor alert (Suggestion of 2 phrases to rephrase).</td></tr>
<tr><td>Phase 3: Evaluation by Human Reviewers
Dr. Chen invites two experts in neuroscience and nutrition. Because AI has already done the technical checks, reviewers can focus on what really matters: the science.</td><td>• Reviewer 1 (Neuroimaging Expert): Doesn't worry about formatting or plagiarism. It focuses directly on the functional magnetic resonance imaging (fMRI) methodology used. In his report, he questions whether the scanning parameters</td></tr>
</table>

	were optimal for detecting subtle changes in neural connectivity. • **Reviewer 2 (Community Nutrition Expert):** Assesses the originality and impact of the study. He notes that while the research is strong, it doesn't adequately discuss how his findings compare to previous studies on nutrition in the same population. It also validates the AI's statistical concern, confirming that the finding is not statistically significant.
Phase 4: Integration of AI-Human Decisions Dr. Chen receives both human checkups. The AI system helps you again. With this synthesis, Dr. Chen's decision is clear and well-founded: **"Major Review."**	• **Consistency analysis:** The AI highlights that both reviewers, although from different angles, question the robustness of the article's conclusions. • **Summary of key points:** Generates a list with main criticisms: (1) Questionable fMRI methodology; (2) Lack of context with existing literature; and (3) Confirmation of statistical error.
Phase 5: AI-Assisted Reviews for the Author Dr. Garcia receives the decision. Along with feedback from reviewers, you receive automated AI suggestions to improve your manuscript. This helps Dr. Garcia perform checkups more efficiently and accurately.	• A language editing tool that helps you rephrase complex sentences. • A reference formatting wizard that automatically corrects both citation errors. • A direct link to Table 2, highlighting the statistical discrepancy that needs to be addressed.
Phase 6: Final Editorial Decision and Publication Dr. Garcia forwards her revised manuscript. The editor, Dr. Chen, verifies that all the main indications have been addressed. The AI performs a final check to ensure that everything is correct. The article is **accepted**. Thanks to this hybrid model, the total time from shipment to acceptance was **3 months**, instead of the 8-10 months it could have taken in a traditional process. The quality of the review was higher because humans focused on deep scientific content, while AI ensured technical rigor and process efficiency.	

3.3.3 Addressing ethical concerns and reviewer trust in AI

While AI enhances speed and objectivity, concerns remain about over-reliance on automation. Key ethical challenges include:

- Transparency: Journals must ensure that AI decisions are explainable, prevent ing the "black box" effect where editorial decisions lack justification [49].

- Algorithmic bias: AI models must undergo constant retraining to minimize biases inherited from historical publishing trends [50].
- Reviewer perception: Studies indicate that many academics remain skeptical of AI-generated reviews, fearing that it may devalue expert judgment and lead to deskilling [51].

To mitigate these risks, guidelines for responsible AI integration must be developed, ensuring that AI complements rather than replaces human expertise in scientific evaluation.

It should be noted that the proposed model is in line with the principles of COPE (Committee on Publication Ethics), the UNESCO Recommendations on the Ethics of AI, ALLEA (All European Academies) and the ICMJE (International Committee of Medical Journal Editors).

COPE determines that authors and reviewers are responsible for the content of manuscripts and that any use of AI must be declared. The purpose of the use of AI is to support the review, but critical assessment and acceptance decisions are human nature. UNESCO determines that humans are the ones who have control over AI. AI generates reports and suggestions, but editors and reviewers are the ones who validate them. AELLEA's European Code of Conduct, revised in 2023 for the introduction of AI, includes principles such as the implementation of models that improve effectiveness, fairness and integrity in the review process that does not only fall on overburdened voluntary reviewers. The ICMJE requires authors to declare whether they have used AI technologies in their manuscript, and the journal itself must be transparent in the evaluation of the papers, maintaining an ethical standard for all participants, and especially if AI is used for peer reviews.

4. Estimation of peer review and publication timeline: Comparison between the traditional model and our proposal

One of the key challenges in scientific publishing is the length of the peer review process. Estimating the time required for different stages of manuscript evaluation provides insight into potential improvements with AI-assisted peer review. The estimated time for peer review and publication in the current system varies. The time to first editorial decision (initial response after submission) typically takes between 2 and 8 weeks in traditional journals, whereas high-efficiency and open-access journals may respond within 1-4 weeks [2]. For this article, the estimated response time is 4-6 weeks, considering the relevance of AI in peer review and reviewer availability. The time to final acceptance, from submission to final approval after peer review, depends on journal policies. Standard peer-reviewed journals generally take 3 to 6 months, while high-impact journals may extend beyond 12 months [9]. Some fast-track or alternative review models, such as pre-prints or accelerated reviews, can take as little as 1-3 months. The estimated time for this article is 4-8 months, depending on the number of review rounds and the speed of reviewer feedback. Once accepted, the time from acceptance to final publication also varies. Early online publication, such as pre-proof or ahead-of-print versions, can occur within 2-4 weeks after acceptance [47]. The final publication in an official journal issue, however, can take anywhere from 1 to 6 months, depending on journal production schedules [28]. For this article, the estimated publication time is 2-3 months for early online access and 4-6 months for final journal release. The total estimated timeline, from submission to final publication, depends on the journal type. In an optimistic scenario with efficient or open-access journals employing an accelerated review, the process may take 6-9 months [22]. In a standard scenario following the traditional peer review model, the timeframe ranges from 9-14 months. In a delayed scenario, particularly in high-impact journals with extensive review and editorial delays, the process could extend to 12-18 months. The AI-human hybrid peer review model proposed in this article has the potential to significantly reduce review and publication timelines by optimizing key stages. The first editorial decision could be shortened to 1-2 weeks instead of 4-8 weeks. The time to final acceptance could be reduced to 2-4 months instead of 4-8 months. The time from acceptance to publication could be minimized to 1-2 months instead of 2-6 months [24]. In the current system, the estimated total publication time for this article would range from 9 to 14 months in a traditional journal. However, implementing the proposed AI-assisted peer review model could potentially reduce this to 4-8 months, significantly enhancing the efficiency and speed of scientific publishing while maintaining rigor and integrity.

On the other hand, one of the key economic benefits of implementing a hybrid AI-human peer review system is the reduction of operational costs. Traditional peer review relies heavily on volunteer reviewers, leading to indirect expenses such as editorial workload, administrative management, and publication delays, which affect journal profitability [2]. AI can automate initial screening tasks, such as plagiarism detection and format compliance, reducing administrative burdens and cutting editorial costs [9]. Additionally, the acceleration of the publication process can lead to increased revenue for journals. In the traditional model, peer review can take between 3 and 12 months, delaying publication and limiting journal throughput [47].

A hybrid model could shorten this timeline to 4-8 months, allowing more articles to be published annually, thereby enhancing journal competitiveness and financial stability [28]. Another economic advantage is the reduction of reviewer fatigue and turnover. Many human reviewers decline requests due to workload pressures, affecting the overall quality and consistency of the peer review process [24]. AI can alleviate this by conducting preliminary technical evaluations, enabling human reviewers to focus on assessing the manuscript's novelty and scientific contribution. This would lead to lower recruitment costs for journals and improved retention of expert reviewers. Furthermore, the hybrid model reduces the cost per manuscript review. Traditional review requires assigning multiple experts, which results in prolonged evaluation times without guaranteeing acceptance. By leveraging AI for preliminary assessments, journals can significantly reduce per-manuscript review costs by 30-50% [52]. Finally, implementing AI in peer review increases transparency and reduces costly errors. Human reviewers are susceptible to biases and errors that may result in low-quality publications or article retractions, which can damage a journal's reputation [8]. AI can systematically detect ethical issues, plagiarism, and statistical errors before human review, improving the reliability of published research and avoiding post-publication corrections [53].

Table 2 presents a realistic scenario, considering the data provided in the previous paragraphs, concluding that the hybrid model offers benefits both economically and in terms of efficiency (review and publication times are drastically reduced), quality and scientific rigor (greater consistency in the evaluation, better detection of errors and plagiarism; and reduction of algorithmic biases if the AI is trained properly) and sustainability (reduction of of reviewer fatigue and optimization of editorial resources).

Table 2. Comparison of costs and benefits of the traditional scientific review model with respect to the hybrid AI-human model.

Features	Traditional Model	AI-human hybrid model	Differences
Final acceptance time	6 months (180 days)	2-months (60-120 days) 33-66% reduction	FASTER
Time from acceptance to publication	1-2 weeks	2-6 months	FASTER
Cost per manuscript	2000€ (approximate average)	1,175€ Reduction between 30-50%	CHEAPER Reduction of €825 (41.25%)
Editorial workload	High	Significantly reduced	LOWER LOAD
Auditor fatigue	High Delays and negative ratings	Reduced, focusing humans on critical tasks	LESS FATIGUE
Error/plagiarism detection	Manual or with basic tools, less efficient	Automated, faster and more comprehensive	MORE EFFICIENT
Consistency in Evaluation	Variable by human subjectivity	Greater consistency by AI predefined criteria	MORE CONSISTENT
Publication volume	Limited by process efficiency	Increased ability to publish more articles per year	INCREASED VOLUME
Reputation of the journal	Vulnerable to errors	Enhanced by greater rigor and less likelihood of errors	CHAIR

5. Conclusions

The introduction of AI in peer review represents a radical shift in academic publishing, offering unprecedented improvements in efficiency, consistency, and objectivity. However, technical, ethical, and trust-related barriers must be addressed before full-scale adoption. Rather than viewing AI as a replacement for human reviewers, it should be seen as a complementary tool that enhances the evaluation process. The most effective strategy moving forward will likely involve a hybrid AI-human peer review model, balancing automation with human expertise to create a more transparent, fair, and efficient scientific publishing ecosystem. Ensuring that AI-based peer review systems are fair, explainable, and rigorously tested will be key to building trust and facilitating widespread acceptance in academic communities. The future of AI in peer review is not about removing human judgment but about enhancing the capabilities of editors and reviewers to create a more equitable and efficient scientific review system. Additionally, from an economic perspective, the hybrid AI-human peer review model is more sustainable and profitable than the traditional model. It reduces operational expenses, accelerates publication times, optimizes reviewer efforts, lowers per-manuscript costs, and enhances transparency. These improvements make AI-assisted peer review an essential strategy for modernizing and increasing the efficiency of academic publishing.

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