Authorship and Peer Review in the Era of Artificial Intelligence

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This article presents an overview and discusses the future of authorship and peer review, considering the recent advances in using Artificial Intelligence.

Authorship and peer review are at the core of science, technology, engineering and mathematics (STEM) and play crucial roles in other disciplines such as health, social sciences and humanities. Peer review, in particular, as the process of collecting knowledgeable third-party opinions about the nature and quality of specific value propositions for informed decision-making or advice, is an essential part of the research cycle and a relevant economic activity. Indeed, according to a survey by Publons [1], the top 20 public funders had a US$ 126 billion budget in 2019, accounting for nearly 7% of the global R&D funding and corresponding to about 30% of the peer-reviewed funded research that year.

Even though authorship and peer review have reached a high level of maturity, they are still susceptible to the benefits and drawbacks of employing Artificial Intelligence (AI). AI is digitally transforming our society, many economic sectors and especially information technology [2]. Several initiatives already use AI-based tools for authorship support, plagiarism detection, compliance and validity checking, and reviewer-manuscript matching and scoring. However, some of these initiatives appear controversial and have been received skeptically by funders and experienced reviewers [3,4]. Moreover, using AI tools to assist in formulating value propositions raises severe concerns about ethics, fairness, transparency and accountability.

This article presents a broad overview and discusses the future of authorship and peer review, considering the recent advances in using AI. The article focuses (not exclusively) on STEM and some reasonable questions that have been frequently asked: i) How can peer review avoid the perils of using AI in authorship? ii) How can AI be effectively used to attain the objectives of peer review? It is evident that analyzing the current challenges and opportunities for peer review and authorship in the era of AI is timely and convenient. However, this requires an *a priori* refined understanding of the peer review process and the nature of AI systems, which is developed below.

On the Structure of the Peer Review Process

The most well-known instance of the peer review process deals with manuscripts detailing scientific research. In the role of authors, researchers from industry, government or academia must highlight the value propositions that correspond to their most important scientific contributions in their papers. Volunteer experts without conflicting interests with the authors should produce reviews that will help improve the reported research while providing sufficient information for editorial decision-making. In this case, peer review is adopted in editorial workflows to assist journal editors and conference organizers reach critically informed decisions on whether submissions should be published [5]. These decision-makers are also responsible for the hard work of selecting reviewers and sourcing reviews. This publication process is how the scientific community identifies original high-quality research.

Grant peer review is a similar process. A grant is a financial award given to an individual, group or organization to fund a research project [1]. Usually, a funder awards a grant provided there are consensual and positive third-party reviews about a submitted research project, which captures the value propositions identified by its authors while planning their research. In this case, external experts offer their services voluntarily or for a financial compensation to produce reviews. Based on the reviewer recommendations, funders contrast project strengths and weaknesses with their policies and select the projects for funding considering risk sharing, the efficient application of the available budget and diverse other criteria. This grant-review process is how research funders choose the most competitive and promising projects to ensure innovative R&D or scientific development.

There is another situation in which peer review is adopted in organizations. Consider the example of national statistics institutes in need of formal feedback on whether their processes comply with international statistical manuals, standards and best practices. In this case, staff from other institutes serve as reviewers to ensure the statistical institute processes quality. Online discussions and in-person meetings establish peer-review panels and personal connections. This interactive process fosters knowledge transfer by identifying benchmarks and sharing best practices [6]. Through this process, national offices ensure statistical quality and relevance through process improvement and innovation. Peer review is particularly important for national statistics offices due to the increasing demand for timely, comprehensive, reliable, accessible, comparable and relevant official statistics in the context of frequent changes to reporting requirements, staff turnover and budget restrictions [7].

Table 1 provides a comparative overview of the most usual peer review processes. As noted, there are many commonalities and some differences between these processes. There is a consensus that peer review is complex and time-consuming [3], mainly to find expert reviewers, write high-quality reviews and recognize this work [1,5]. A common deviation from the typical peer review process is when there are not enough reviews or the recommendations are conflicting [8]. Nevertheless, peer review requires explicit guidelines and training [1,5,6,7] and ensures transparency and accountability for all the involved people [6,7]. Pre and post-process peer review are also possible but are out of the scope of the present article.

On the Public Nature of Artificial Intelligence

State-of-the-art AI systems have been used by authors, reviewers and other stakeholders thanks to the open-access policy maintained by leading software companies and open-source projects developed by the academic community. Even though enthusiasm surrounds the public availability of some AI systems, there are serious concerns about their trustworthiness. In a response attempt, standardization bodies, multilateral organizations and legislative houses have respectively produced standards families, policy recommendations and technology regulations to foster AI usage, governance and trust [9].

The International Standards Organization (ISO) is working on a set/family of foundational standards to define common terminologies and critical concepts to artificial intelligence, machine learning and natural language processing (NLP) tools. These standards focus not only on general terms but also on trustworthiness. In particular, the ISO 22989 standard provides a functional overview of AI. It defines AI systems as engineered systems that generate outputs such as content, forecasts, recommendations or decisions for a given set of human-defined objectives [9]. The standard also covers the AI system life cycle: the development, deployment and use of AI systems.

The ISO 22989 standard suggests the adoption of the following principles to ensure AI trustworthiness:

- Autonomy: The actions or processes of an AI system are allowed to take place without the need for natural persons to be directly involved in their execution.
- Predictability: Stakeholders can make reliable assumptions about the outputs produced by an AI system.
- Explainability: It is possible to identify factors influencing the outcomes of an AI system in ways that humans can understand.
- Transparency: The relevant AI stakeholders receive all the required information.
- Non-discrimination, bias-avoidance and fairness: There are restrictions in the systematic differentiation of treatment of particular objects, people, or groups by an AI system compared to similar entities in order to avoid inequality, bias and discrimination.

There are other higher-level principles that aim to promote innovation and build trust in AI. The Organization for Economic Co-operation and Development (OECD) coined the following additional foundational principles to ensure confidence in AI systems [10]:

- Accountability: AI actors should be accountable for the proper functioning of AI systems.
- Human-centered values: AI actors must respect values that include freedom, dignity and autonomy, diversity, social justice, and internationally recognized labor rights.
- Inclusive growth, sustainable development and well-being: Stakeholders should proactively engage in the responsible stewardship of trustworthy AI in pursuit of beneficial outcomes for human society and the planet.

It is worth mentioning that other principles have also been formulated – such as security, safety, robustness, reliability and resilience – but these are primarily connected to the realization of AI systems in the form of software. It is also interesting to note that the development of legislative processes usually considers all these principles.

Suppose we abstract away the focus on AI systems and stakeholders from the above principles. In that case, they can be applied equally well to R&D, scientific research, process improvement, and peer review. As discussed in the following sections, compliance with the low-level and high-level principles above allows us to identify how to counter identified challenges and exploit existing authorship and peer review opportunities connected to AI.

Top Challenges to Authorship and Peer Review in the Era of AI

An analysis of the latest literature can provide valuable insights into how the utilization of AI in peer review and authorship poses challenges to the identified principles:

Introduction of Algorithmic Bias by AI in Research. AI systems often use machine learning models that depend on previous results to predict and generate outcomes [3]. Such models may introduce algorithmic bias in research outcomes that are difficult to identify during peer review. For example, training sets with data gaps covering different population groups may lead to biased analyses, which only refined outcome stratification may locate. These biases could cause unfair treatment and discrimination against certain groups. When biases are discovered after research results have been financed or published, it harms the credibility of the entire peer review system. Retraction is a palliative solution in the case of publications. Despite the fact that retraction rates are increasing [5], it is unclear right now the contribution of algorithm bias generated by AI to this situation.

Use of Generative AI in Authorship. Some scientists, engineers and statisticians already use large language models to help organize their thinking, generate feedback, assist with writing code and produce literature summaries. Although using chatbots as assistants is sometimes convenient, this may introduce errors, reduce process and research transparency and infringe third-party rights. Worse still, it can be used as an excuse to avoid accountability in authorship and undermine human-centered values and inclusiveness. For these reasons, the editors of Nature, Science and Elsevier journals concluded that texts and images uniquely generated by chatbots cannot be accepted as original pieces of work for publication [11,12,13], nor can chatbots be considered credited authors on research papers [11,13].

Stakeholder Misconduct with AI. In addition to facilitating the deliberate inclusion of biases in research activities, AI systems can make other malicious outputs easier to produce. Chatbots based on large language models can create texts and code that sometimes knowingly cannot be trusted [11], and other AI systems can quickly produce manipulated pieces of sound or image [3,12]. Datasets can also be fabricated or analyzed by AI systems in clear violation of ethical principles. Adopting such opaque data and malicious automatic procedures for knowledge generation challenges peer review fairness critically [11].

AI-based Verification of Validity, Accuracy or Reliability. Developing research results and improving statistical processes considering the published literature is common practice. The adopted reporting methods typically disclose taxonomies, classifications, methods and techniques of analysis, existing threats to validity (including risks of bias), research results or process improvements, and conflicts of interest. Studies should expose incentives for stakeholder participation and limitations on research data and findings. Historically, these practices have been verified manually (see [14] for an example of systematic analysis).

It is now possible to employ NLP techniques for this kind of verification [4,15]. Some AI tools can suggest appropriate verification tests for the validity and reliability of research results [16]. For example, the Scite.ai, StatReviewer and Statcheck tools help check the validity, statistical soundness and consistency of research results reported in manuscripts [3,17]. However, the misguided use of such AI tools or their application out-of-context (for example, in evaluating the processes of national statistics offices) challenge the autonomy and ethics of peer review [4]. It introduces unacceptable risks in quality assurance in connection to peer review.

Introduction of AI in Advice or Decision-Making Processes. Through machine learning algorithms, it is already possible to develop AI systems that assist humans in peer review decision-making processes. However, the underlying models may propagate cultural and organizational biases in learning sets. For example, AI can adversely affect decisions on the publication of papers produced by authors from low-income countries or those on innovative topics, as the manuscripts in these circumstances may not have been adequately considered in training sets [3,15]. These tools may have also been trained with previously rejected papers. Moreover, AI tools often have difficulties with ambiguous texts. As an example, the experiments detailed in [17] reached a maximum precision of just 43% in reading a given set of papers, identifying their key concepts, organizing their keywords by type, and identifying existing relationships.

Consequently, the recommendations produced by AI systems may adversely influence the mindset of funders, editors and reviewers. AI tools may suggest that editors and funders preserve previous authority and avoid change in the *status quo* using biased training sets [3]. Reviewers may be erroneously chosen and may not be able to produce the best possible information due to incorrect or poor keyword classification or correlation [17,18]. Moreover, authors may preemptively change their behavior when they know fully autonomous agents will assess their value propositions [15]. So, the sole adoption of AI systems for peer review decision-making or advice may challenge this process's autonomy, predictability and transparency.

Top Opportunities for Using AI in Authorship and Peer Review

The latest literature also reports the following opportunities for authorship and peer review due to the use of AI:

Automated Insight Generation. Admittedly, AI systems are good at interactively generating insights for scientific research and process improvement. AI solutions such as Cactus Communications' UNSILO and ChatGPT can summarize the contents of manuscripts [3,19], while the latter is also helpful for brainstorming by conversationally using chatbots [19]. Tools like Elicit.org and ChatGPT, in addition, can survey the literature and determine which research questions remain open [12,17]. These practices enforce research autonomy and encourage creativity by including in the respective agendas practical themes, developments and prosperity that might not have been foreseen otherwise.

Improved Reporting and Submission. Likewise, AI systems are excellent tools for enhanced reporting, mainly through NLP models that output readability formulas and cognitive indices [3]. These tools can be used during document preparation to assist in improving the readability of draft versions [19] or for fixing formatting and quality of argumentation issues [3].

Another area in which AI may help is in determining the best venue for a manuscript submission. Typically, this task is reserved for conference organizers, journal editors and leading members of scientific communities willing to share their experience in writer workshops or paper shepherding processes. In these situations, AI can match draft article contents to publication venue profiles in order to determine recommendations of the most suitable venues [18].

In both cases, AI systems may contribute to more explainable and transparently reported research and quality assurance results, and increase the likelihood for authors of achieving desired results, be they the publication, funding or improvement of their value propositions.

Initial Compliance Checking. Editorial, funding and quality assurance guidelines usually drive peer review. These guidelines cover content and formatting instructions for scientific manuscripts, research projects and statistical process quality assurance questionnaires. Not surprisingly, AI systems can determine whether or not a piece of work under consideration meets the requirements in these guidelines [15]. For example, one can extract derivable rules from the given guidelines using decision-tree or random-forest algorithms [20] and run checks of scope and compliance against the given formatting instructions and subjects of interest using neural networks [3]. In doing so, AI systems can improve predictability, accountability and reduce bias in peer review processes.

Reviewer Matching. AI systems can also help suggest manuscript-reviewer matches. Automated matching is possible by using databases of reviewer profiles containing backgrounds, preferences and affiliations to identify best-suited reviewers for each task [15,18] while attempting to prevent conflicts of interest [3]. In particular, these tools can use online repositories [18] and social network links [15], apart from the keywords included in submitted documents [4]. Then, it is possible to use diverse AI-based textual analysis, classification and correlation algorithms for these analyses. Examples are feature-based matching (based on keywords), profile-based matching (based on reviewer and paper profiles derived from the textual representation of their characteristic features) and reviewer bidding (based on declared reviewer preferences and conflicts of interest) [18]. While up-to-date conference management systems such as www.easychair.org already support reviewer bidding schemes, some conferences have adopted alternative hybrid interactive methods to enhance the peer review process even further. So, human-led AI-based reviewer matching has increased the predictability of the process while reducing possible biases in reviews.

Conflicts of Interests Prevention and Detection. Another area in which AI systems can help is detecting conflicts of interest that could go unnoticed [4]. Conflicts occur when professional misjudgment or unduly influences may happen due to secondary interests connected to stakeholder affiliations, funding sources, and supply and demand relationships, typically related to the adopted data or technologies [14]. Unfortunately, conflicts of interest are challenging to detect due to the lack of transparency in reporting and their origin in diverse and indirect sources, not only on the author's side but also between reviewers and authors. With NLP matching, hierarchical clustering disambiguation and link merging algorithms, it is possible to expose existing conflicts, also relying on integrating other sources that would not have been considered otherwise, such as data on the web [16]. The prevention and detection of conflicts of interest increase fairness in peer review while reducing possible biases in judgments.

Plagiarism Detection. AI systems are also helpful in plagiarism detection. Some of these tools, implemented using text analysis techniques, can identify and flag papers with similar-sounding paragraphs, sentences, and entire pieces of copied text. For instance, the crosscheck.ieee.org portal can be used by IEEE members to compute paper similarity scores and keep a list of authors who have been banned from publications due to violations of IEEE publishing conduct guidelines. Other AI systems can spot manipulated images or whose original authors have not received credit [4].

However, this practice is not straightforward to implement because AI tools can be fooled through synonyms or paraphrasing [16]. When it comes to self-plagiarism, the analysis becomes even more subjective as the amount of allowed text replication varies depending on the editorial policies of the respective publications. These situations illustrate that, as a rule, human intervention is necessary.

Nevertheless, AI-based plagiarism detection contributes to fairness and enforcing human values in peer review.

Fraud Detection. Machine learning algorithms can flag whether or not there are serious data gaps or research data that has been omitted on purpose, has been unduly modified or has been generated to achieve a desired outcome [16]. Despite the current availability of fraud detection algorithms, detection models still need to be appropriately calibrated on a case-by-case basis, possibly considering composite metrics using precision and recall indicators [20]. This practice contributes to enforcing fairness and human values in peer review.

Improved Process Transparency. Some AI systems can detect the presence in manuscripts of the transparency statements required by publishers [15], such as data availability, author contributions, conflicting interests and funding sources. Based on local interpretable model-agnostic explanations [3], machine learning systems can provide to researchers who have submitted their work written synthetic justifications of decisions made by publishers or funders. These explanation systems can consider past review decisions via data-driven predictors/classifiers. Thus, this practice contributes to peer review explainability.

Improved Process Productivity. AI tools can expedite review processes by integrating compliance checking, reviewer matching, conflict of interest, plagiarism and fraud detection to form peer review support systems. These integrated AI systems can potentially increase peer review predictability, save the working hours of editors and reviewers and uncover possible biases [3]. An example is the simulation platform based on Cartesian Genetic Programming described in [8] that can generate evolved review strategies. The platform uses simulation data to optimize the review process by streamlining editor workflows and reducing review time.

Better Informed Decision-Making. Editors and managers, respectively, acting on behalf of publishers and funders, can benefit from AI-based decision support systems [3] integrating all the features above. In particular, these AI systems can detect the lack of transparency in articles submitted for publication by identifying critical missing information for decision-making required by editorial or funding policies, such as frequency distributions, sample sizes, missing data treatment and statistical errors [14,16]. Another possibility is using AI systems as rudimentary tools to model human behavior since they can reveal the extent to which human decision-making may use different quality proxy measures, which could produce inequitable assessments [3]. This way, AI creates opportunities for improving peer review in all aspects.

Dealing with Challenges and Opportunities

Considering the challenges and opportunities presented in Fig. 1, how have authors, decision-makers and statistics office staff answered the questions posed in the introduction?

To counter the excessive use of generative AI in authorship, one of the two most frequently cited challenges to peer review, scientific publishers have updated their editorial policies to make clear that text, code, images, graphics and other media generated by AI are not acceptable as original pieces of work and shall not be published [11,12,13]. In particular, Springer Nature is now developing new technologies to detect AI-generated textual output [11]. Publishers have also included in authorship guidelines that any AI-generated material must be carefully checked [19] and transparently reported in submitted manuscripts [11,13]. Indeed, most cases of scientific misconduct have occurred due to inadequate human attention [12]. Moreover, publishers have strengthened their compliance requirements with data availability, author contribution and conflicting interests reporting procedures to ensure that research data is trustworthy, natural persons are accountable for reported results [12], the usage of AI is transparently disclosed [13], and risk of bias mitigation procedures exist. Funders have also updated their guidelines, focusing more on preventing conflicts of interest when assessing research proposals [4].

The second most frequently cited source of challenges for peer review is the indiscriminate introduction of AI in advice or decision-making processes. In this case, publishers, funders and national statistics offices have used AI tools while stressing that human oversight is fundamental in these activities. The Springer Nature publications have adopted AI tools to fight malpractice, including paper mills, fabricated results, duplicate submissions and plagiarism [19]. Elsevier uses AI in the Evise system to check for plagiarism, recommend reviewers, and verify author profile information against the contents of Scopus [15,17]. The Frontiers publisher has developed an AI system to analyze scientific papers and identify 20 research integrity issues [4]. Among research funders, the Science Foundation of São Paulo State, Brazil (FAPESP), uses AI systems to suggest the best-suited reviewers to assess submitted grant proposals [4].

Regarding the identified opportunities, better-informed decision-making is the most frequent citation. It corresponds to adopting an integrated framework for exploiting specific opportunities of using AI systems in peer review. The focus here is not on a total replacement for human input in peer review but on how different tasks can be delegated or refined through automation [15] while ensuring transparent rationales for decision-making. Publishers and grant providers are exploiting this kind of opportunity by integrating existing tools like those mentioned above.

Apart from the macro-opportunity above, which is solely related to decision-making, it is worthwhile mentioning that national statistics offices have also exploited the opportunities generated by AI in authoring and reviewing statistical processes. The United Nations Economic Commission for Europe (UNECE) is working on a quality assessment framework for supporting the development and acceptance of machine learning algorithms in statistical processes [20]. The framework relies on the joint application of the quality dimensions of accuracy, explainability, methods reproducibility, timeliness and cost-effectiveness for algorithm selection. Equally important are the acceptance criteria for machine learning algorithms, based on the critical factors of alignment with business needs, respect to human values, demonstration of value-added, scientifically grounded development and presentation of robust performance. Adopting this framework facilitates statistical process authoring, peer review, improvement and modernization.

What is Next?

The cases reported in the previous sections provide evidence of substantial improvement in authorship and peer review due to the adoption of AI systems. There is still room for improvement in these processes as they are right now. Subjects that have yet to be addressed with AI systems include author encouragement for addressing complex or innovative topics [1] and effective reviewer recognition [1,5]. Another subject that concerns most authors, editors and funders is ensuring enhanced scientific impact [1]. Forthcoming strategies to approach enhanced impact issues using editorial systems based on AI should foster insight generation and creativity in authorship, and enforce explainability, friendliness and other human values in peer review, for example, by implementing AI systems based on risk-reward procedures so that, on the one hand, authors feel more compelled to address innovative and complex subjects, and, on the other, reviewers receive stimuli for producing nuanced and thoughtful feedback.

Authorship and peer review constantly evolve, so it is reasonable to consider AI's contribution to reshaped processes. For example, the continued digitization of scientific publications relying on AI may lead to innovative user experiences [2,5]. Packing peer-reviewed research datasets, reported analyses and results together with knowledge generators tends to conform trustful modular systems based on intelligent agents with which users can interact [17]. In this case, the limitations of these systems should be transparently disclosed to make it clear that they will not be able to circumvent undecidability constraints. AI systems can also make editing and publishing more interactive and conversational while reducing the risks of plagiarism, fraud and lack of accountability, leading to improvements throughout the process. Increased augmented communication between authors and decision-makers, and between them and reviewers, is vital to fostering trust among all parties involved. Some research publications have already adopted this editorial approach (see [15] for an example), but still only a few rely on AI.

Furthermore, socially admissible AI systems may be defined and enforced, potentially affecting authorship and peer review based on AI. A reasonable route to realizing this admissibility view is through legislative processes. New legislation may help ensure bias monitoring, detection and correction in AI systems, mitigating the respective risks [21]. From the point of view of AI stakeholders in authorship and peer review, as natural persons, it may be convenient to enforce the following fundamental rights through new legislation on AI systems:

- know in advance that interactions will be done directly with an AI system;
- obtain an explanation of the adopted criteria and rationale that lead to any AI-based decision, recommendation or forecast;
- ability to identify the entity in charge and challenge any decision performed in an automated way through AI;
- request human intervention in any process conducted solely by AI;
- guarantee that new AI legislation is consistent with current laws and regulations while ensuring legal certainty;

The European Parliament and Brazilian Congress now discuss legislative acts covering these rights [21,22]. National statistics offices are expected to participate in these discussions in what concerns official statistics.

Admittedly, peer review is among the most reliable methods for scholarly reading, citing, and publishing [23] and for statistical process quality assurance. Our findings indicate that authorship and peer review should continue mainly by humans but with increasing assistance and guidance from AI systems. Enhanced AI systems are welcome and important as long as they produce value-added [20] and less error than systems solely governed by humans [15], never losing sight that AI tools should serve people in posing hypotheses, designing experiments, and making sense of results [12], but never the opposite. It is difficult to predict the future, but many more changes will likely be introduced in authorship and peer review through AI. In times to come, AI itself may explain to us.

DISCLAIMER

The assumptions, views, and opinions in this article are solely those of the author and do not necessarily reflect the official policy, strategy, or position of any government entity.

REFERENCES

1. Web of Science Group. *Grant Review in Focus*. Global State of Peer-Review Series. Clarivate Plc. London, UK. Oct. 2019. Available: https://publons.com/static/Grant-Review-in-Focus-web.pdf (accessed Mar. 3, 2023)

2. Ebert, C. and Duarte, C. Digital Transformation. *IEEE Software* 35 (4):16-21. Jul. 2018. doi: 10.1109/MS.2018.2801537
3. Checco, A. et al. AI-assisted Peer Review. *Humanities and Social Science Communications* 8(25). Jan. 2021. doi: 10.1057/s41599-020-00703-8
4. Marques, F. Artificial Intelligence in Peer-Review. *Pesquisa FAPESP* 299:8-9. Jan. 2021. Available: https://revistapesquisa.fapesp.br/en/artificial-intelligence-in-peer-review/ (accessed Mar. 11, 2023)
5. Web of Science Group. *Global State of Peer-Review*. 2018. Clarivate Plc. London, UK. Sept. 2018. doi: 10.14322/publons.GSPR2018
6. European Union Statistical Office (Eurostat). *European Statistical System Code of Practice Peer Reviews: The National Statistical Institute's guide (Version 1.3)*. Mar. 2007. Available: https://ec.europa.eu/eurostat/documents/64157/4372828/NSI+peer+review+guide+1.3.pdf (accessed Mar. 11, 2023)
7. Organization for Economic Co-operation and Development (OECD). *DAC Peer Review Reference Guide.* Mar. 2017. DCD/DAC(2017)10. Available: https://www.oecd.org/dac/peer-reviews/DAC-peer-review-reference-guide.pdf (accessed Mar. 11, 2023)
8. Mrowinski, M. J. et al. Artificial Intelligence in Peer Review: How Can Evolutionary Computation Support Journal Editors? *PLOS One* 12(9): e0184711. Sept. 2017. doi: 10.1371/journal.pone.0184711
9. International Organization for Standardization (ISO). *Information Technology — Artificial Intelligence — Artificial Intelligence Concepts and Terminology*. ISO/IEC 22989 Standard. Geneva, Switzerland. Jul. 2022. Available: https://www.iso.org/standard/74296.html (accessed Apr. 8, 2023)
10. Organization for Economic Co-operation and Development (OECD). Recommendation of the Council on Artificial Intelligence. May 2019. OECD/LEGAL/0449. Available: https://legalinstruments.oecd.org/en/instruments/oecd-legal-0449 (accessed Mar. 3, 2023)
11. Tools such as ChatGPT Threaten Transparent Science. *Nature* 613, 612:612. Jan. 2023. doi: 10.1038/d41586-023-00191-1
12. Thorp, H. ChatGPT is Fun, But Not an Author. *Science* 379, 6630:6630. Jan. 2023. doi: 10.1126/science.adg7879
13. *The Use of AI and AI-assisted Writing Technologies in Scientific Writing.* Available: https://www.elsevier.com/about/policies/publishing-ethics/the-use-of-ai-and-ai-assisted-writing-technologies-in-scientific-writing (accessed Aug. 20, 2023)
14. Duarte, C. Software Productivity in Practice: A Systematic Mapping Study. *MDPI Software* 1(2):164-214. May 2022. doi: 10.3390/software1020008
15. Tennant, J. P. et al. AI-assisted Reer Rreview. A Multi-disciplinary Perspective on Emergent and Future Innovations in Peer Review. *F1000Res* 6(1151):30-31. Nov. 2017. doi: 10.12688/f1000research.12037.3
16. DeVoss, C. Artificial Intelligence Applications in Scientific Publishing. *What might peer review look like in 2030?* BioMed Central and Digital Science. London, UK. May 2017. pages 4-6. doi: 10.6084/m9.figshare.4884878
17. Stockton, N. If AI Can Fix Peer Review in Science, AI Can Do Anything. Feb. 2017. Available: https://www.wired.com/2017/02/ai-can-solve-peer-review-ai-can-solve-anything (accessed 20th Aug. 2023)
18. Price, S. and Flach, P.. Computational Support For Academic Peer Review: A Perspective from Artificial Intelligence. *Communications of the ACM* 60(3):70-79. Mar. 2017. doi: 10.1145/2979672
19. The AI Writing on the Wall. *Nature Machine Intelligence* 5, 1:1. Jan. 2023. doi: 10.1038/s42256-023-00613-9
20. United Nations Economic Commission for Europe (UNECE). *Machine Learning for Official Statistics.* Geneva, Switzerland. Mar. 2022. Available: https://unece.org/sites/default/files/2022-09/ECECESSTAT20216.pdf (accessed 13th May, 2023)
21. European Commission. *Artificial Intelligence Act*. Apr. 2021. Available: https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX:52021PC0206 (accessed Aug. 20, 2023)
22. Brazilian Congress. *Bill Number 2338/2023: Provisions for the Use of Artificial Intelligence.* May 2023. Available: https://www.congressonacional.leg.br/materias/materias-bicamerais/-/ver/pl-2338-2023 (accessed Sept. 10, 2023)
23. Nicholas, D. et al. Peer Review: Still King in the Digital Age. *Learned Publishing* 28:15–21. Jan. 2015. doi: 10.1087/20150104

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TABLE 1. Situations in which peer review is extensively adopted
(first four columns related to authorship, last four columns related to reviews)

Form of Value Proposition (what)	Authorship (whose)	Maturity Level (how mature is the proposition)	Purpose (why)	Methods (how)	Context (where)	Reviewers (who)	Timeline (when)
Research project	Scientific or R&D investigators	Low to Medium	To obtain research funding	Contrasting the project's strengths and weaknesses to the funder policies and considering the efficient allocation of the available budget	In grant peer-review panels or individual assessments	Researchers working for funding agencies	As soon as the project is ready and funding agencies are willing to accept new submissions
Scientific article	Academic, industrial or government researchers	Medium to High	To publish high-quality research	Ensuring that the research described in the manuscript is original and impactful	In editorial processes of journal or conference proceeding publications	Research peers	Whenever the research is considered ready for publication, considering the respective deadlines in calls for papers
Rigorous assessment of statistical processes	Statistical institutes	High	To obtain feedback and advice on statistical processes quality	Verifying whether or not the current practices comply with international statistical manuals and best practices	Personally, in remote discussions and face-to-face visits	Experts from other statistical institutes	Periodically, particularly before substantial changes in statistical processes

Figure 1. Peer-review challenges and opportunities in relation to identified principles
(challenges and opportunities identified in the literature, connection to principles elaborated by the author)