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Research paper

The Impact of Artificial Intelligence on Scientific Research Methodology

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ABSTRACT

Artificial intelligence is profoundly transforming scientific research methodology. It acts as a catalyst for efficiency, optimizing key processes such as the collection, processing, and analysis of vast volumes of data, thanks to automation and cutting-edge algorithms. Beyond optimization, AI introduces fundamental innovations in the scientific approach itself, facilitating the generation of complex hypotheses and assisting in the writing of publications.
However, this revolution raises major challenges. The opacity of models ("black box"), the reproduction and amplification of algorithmic biases, and the risk of "overgeneralization" or "hallucinations" are critical limitations. These issues underscore the importance of careful and ethical use.
AI is not a substitute for human intellect, but a powerful augmentation tool that requires a rigorous framework. To ensure research remains reliable and fair, it is imperative to strengthen transparency, combat bias, and insist on critical validation by researchers.

Introduction

AI continues to have an increasingly important impact on methodology in research, including in the collection, analysis, and interpretation of data. Given the overwhelming amount of information and the intricate scientific problems, AI has become pivotal in research to enhance precision and productivity. Nonetheless, such changes bring up important issues such as algorithmic transparency or the potential for bias in data evaluation.
AI has streamlined data collection and management by automating information retrieval processes from massive datasets. It helps scrub and NLP processes to organize data in a systematic manner while enhancing its accuracy by identifying and rectifying errors as well as supplementing incomplete data. Automation helps to do data preparation, saving researchers considerable time and effort.
When it comes to analysing and interpreting data, AI-enhanced capabilities are unlike any other techniques available. Machine learning and deep learning algorithms can reveal trends, find complex patterns, and create predictions within large data sets. These techniques are now widely used in fields such as medicine, social sciences, and physics, providing quicker and more accurate results than traditional methods. In addition, AI also helps eliminate biases and make analyses more reliable and aligned with reality.
AI can also help researchers formulate hypothesis. Algorithms can search through scientific databases to locate the missing pieces of existing knowledge and provide a new direction for research. Models have even been developed to generate hypotheses and put them in hypotheses or theoretical framework based off correlations

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found within data. Furthermore, AI can validate hypotheses with more accurate simulations and modelling, contributing to the overall rigor and improved efficiency of the scientific process.
AI is also a factor for thinking about the writing and presenting of research outcomes. AI text generating tools like GPT models can automate the writing of scientific articles, improve the clarity of publications, and automate formatting. AI data visualization methods can help provide interactive graphical representations which can make research outcomes more accessible and understandable.
Several studies investigated the role of Artificial Intelligence in scientific research. Zawacki-Richter and colleagues (2019) indicate that AI can enhance research processes by automating data analysis and generating new hypotheses. However, there are concerns voiced by some researchers such as D'Amour et al. (2020) regarding the introduction of bias through AI models, and how it can impact results. Marcus and Davis (2022) claimed that better explainability is required of deep learning models for scientists to properly assess the veracity of their conclusions. Further, they posit that deep learning is nearing the limits of what it can do and promote a hybrid approach to broaden the definition of AI through the unification of diverse approaches.
While it may offer many advantages to researchers, the use of AI as a research tool also presents its own barriers. Algorithmic transparency is a critical issue. It was suggested that it is important for researchers to know how models are producing their conclusions. Bias can be introduced into analyses when AI reflects and compounds the inherent biases within the training data. There are also technical skills all this requires before a public contribution to make for automated research. Those researchers who are non-technical fields could potentially require more learning effort than compliance on usage.
Artificial intelligence is especially advantageous when it comes to massive data sets, often referred to as Big Data, or when machine learning can use big data sets and task specific machine learning.
At its best, artificial intelligence acts as a research methodology, but still largely consists of textual analysis. That said, research suggests that artificial intelligence can also be combined with corpus linguistics in large scales (Broersma and Harbers, 2018) and perform research feasibility analysis of a large corpus of archives, photographs, or corporate film. Closures and borders are beginning to open between both methods, as the combined technological capabilities of optical character recognition (OCR) software with deep learning are allowing historical text – with peculiar typographic and printed style features that may also preclude the translator role - to be translated automatically before requiring the specific knowledge of specialized translators, in addition to any manuscript work, too, like Michel Foucault's reading notes located in the Bibliothèque Nationale de France (Massot et al., 2019). These recent technological developments indicate some momentum in favor of improving productivity in archival processes - something every researcher appreciates, given the labor and time constraints that researcher has always had to endure.
Artificial intelligence (AI) has grown to be an acknowledged necessity in scientific research and has partly transformed a range of methodological processes. By streamlining data collection and processing, AI has changed the pace at which researchers are working, as well as creating ground-breaking changes across a myriad of disciplines. However, there are problems with AI and algorithms, such as trust in the methodology, bias, and concerns about transparency with the outputs of the AI. The aim of this paper is to explore the changes by attending to aspects of the advantages and limitations of AI in, and with, research methodology.
This change raises a basic question about to what extent AI is reshaping the methodology of research, and how can scientific rigor be maintained in conjunction with tools that are automating part of the cognitive process? This question becomes particularly significant when we remember that algorithms are often viewed as black boxes, opaque, and likely to replicate the biases already in existence. By undertaking this study, we examine the impact of AI on methodology and (1) what it provides, (2) what it does not provide (and (3) the difficulties it poses).
To explore this issue, we start with a literature review to provide context for studies that mention the use of AI in research settings by providing an overview of top innovations and problems that foreshadow ongoing concerns raised by different authors. We will then explore the areas in research where AI can increase optimization in processes with research workflows aided by AI via tasks such as data collection, processing, and interpretation; finally, we will add some discussion of innovations that AI affords to the scientific process that includes hypothesis generation as well as automated writing. In the end, we will include a brief review of the issues and limits facing the use of technologies in research in conclusion with views on the ethically sound and methodologically appropriate use AI in research.

AI is an incredibly powerful and potentially transformative tool in research methodology, simplifying data collection, data analysis and interpretations, and hypothesis making, while improving the communication of research findings. However, the use of AI should be balanced by ethical and methodological scrutiny to capitalize on the potential advantages of AI whilst minimizing the risks that emerge. The future of research will require scientists to collaborate closely with artificial intelligence to tackle the scientific inquiries of the 21st century.

This possible disruption encourages us to consider whether there will be a new norm in research, more empirically and methodologically rooted. "Quality" in research, is established by socially accepted norms established within the academic community and communicated through doctoral education, research methodology and publication channels. It is therefore essential to examine how AI-driven methodologies evolve and assess their impact on the scientific rigor of research.

1. Review of the literature on the use of AI in research

The integration of artificial intelligence (AI) into scientific research processes is attracting growing interest, both for its promise of efficiency and for the questions it raises. Before analysing its concrete uses and methodological innovations, it is essential to place this development in a historical and theoretical perspective. This first part thus offers an overview of existing work on the subject, tracing the evolution of AI in the scientific field, presenting the main contemporary research on this subject, and highlighting the critical debates surrounding its deployment. Through this literature review, we identify the main schools of thought, the hopes held by this technology, but also the limits and ethical tensions highlighted by researchers.

1.1 The main schools of thought on the use of AI in research

The literature, both scientific and philosophical, on the impact of artificial intelligence on research examines several prominent schools of thought, and while their differences range from technological utopianism to critical scrutiny; they also illustrate tensions as concerns and aspirations that arise through this transformation of scientific practices.

1.1.1 The techno-optimistic current: AI as a driver of scientific progress

The techno-optimist movement believes that AI will fundamentally change how we think of research. They see AI as a tool to enhance researchers' capabilities, hasten the pace of scientific discovery, and expand human knowledge. Algorithms, such as those used in deep learning, digest large amounts of data and generate new hypotheses while dramatically improving the accuracy of analyses. Gary Marcus and Ernest Davis present this vision, in their book Rebooting AI (2019), by arguing that AI could change whole fields of science if the technology is effectively used by making science quicker, more rigorous, and more economical (Marcus & Davis, 2019).

1.1.2 Critical current: vigilance against methodological and ethical deviations

Conversely, the critical school places focus on the dangers of using AI in research focus. Authors from this school point to the opacity of so-called “black box” algorithms, the biases contained in data sets, and the lack of robust mechanisms for verifying the results produced by automated systems. Mittelstadt et al.’s (2016) seminal article, The Ethics of Algorithms, maps these concerns, showing that the lack of algorithmic transparency can threaten fundamental principles of the scientific method, such as reproducibility and falsifiability (Mittelstadt et al., 2016). These critics therefore advocate for more rigorous ethical and methodological oversight.

1.1.3 The Humanist Movement: AI as a Tool Serving Human Intelligence

Between the two previous positions, the humanist movement adopts a balanced approach, considering that AI does not replace human intelligence, but complements it. Machines are seen here as decision-making or cognitive enhancement tools, capable of collaborating with researchers without altering their central role in knowledge production. Ben Shneiderman, in his article "Human-Centered Artificial Intelligence" (2020), proposes a cooperative vision in which AI systems are designed to be reliable, secure, and interpretable, to remain at the service of human and scientific values (Shneiderman, 2020).

1.1.4 The Posthumanist Movement: Towards a Redefinition of Epistemological Roles

Finally, the post humanist movement, emerging from the social sciences and science and technology studies (STS), calls for a rethinking of the fundamental categories of research. It considers that AI profoundly modifies the nature of cognitive processes and the conditions of knowledge production, blurring the boundaries between subject and object, author and tool. Luciano Floridi, in The Fourth Revolution (2014), argues that humanity is undergoing a transformation comparable to those of Copernicus or Darwin: a redefinition of our place in the information universe, where artificial agents become co-actors in the construction of knowledge (Floridi, 2014).

These four schools of thought - techno-optimist, critical, humanist, and post-humanist - offer complementary perspectives for understanding the impact of AI on scientific research. Their comparison sheds light on current debates surrounding machine autonomy, human responsibility, and the redefinition of epistemological norms. It also highlights the importance of interdisciplinary dialogue to integrate AI into research in an ethical, transparent, and intellectually fruitful manner.

1.2 AI as a catalyst for scientific transformation

AI can first be understood as a set of techniques with defined contours. According to Rai et al. (2019), AI refers to a range of techniques that give machines the ability to "perform cognitive functions we associate with the human mind, such as perceiving, reasoning, learning, […] and even demonstrating creativity" (p. iii). In educational sciences, Humble and Mozelius (2019) define AI by emphasizing its multidisciplinary nature, which goes beyond computer science alone.

1.2.1 Accelerating Research Processes: Efficiency Gains Validated by the Literature

The recent media buzz surrounding generative artificial intelligence (AI) such as ChatGPT (Open AI's conversational bot) or its competitors (e.g., Google's Bard) perfectly illustrates the challenges associated with AI in teaching, research, and organizations. The use of intelligent machines poses an economic challenge (in terms of flexibility, simplification, and ergonomics) and a societal challenge (in terms of security and transparency) (Dimitropoulos et al., 2021).

Several studies have demonstrated that AI is profoundly changing research practices, notably by automating complex tasks and facilitating the manipulation of large amounts of data.

Traditionally, data collection, processing, and analysis are time-consuming steps. Sometime back, Wang et al.'s (2020) article about automating systematic reviews showed how AI can substantially reduce time taken to search, collate and extract relevant information. When it comes to data collection, the area that is likely where AI has shown remarkable efficacy. For example, Broussard (2018) on web scraping, Chen et al. (2021) on sensor data analysis. Already we have seen AI collect data at rates, quality and coverage that would have previously only been considered in science fiction. The same applies for optimization of data processing. For the ability of AI to clean, organize, and structure a data set of complexity can be easily forgotten or not obviously acknowledged. Perhaps Kaggle competitions (2023) have successfully illustrated that going through all data pre-processing work is rarely not completed better by machine learning algorithms.

Lastly, AI allows computations and analysis to be accelerated as well as in-depth. Groundbreaking work done in deep learning by LeCun, Bengio and Hinton (2015) has been done, and it exemplifies how AI can find correlations, anomalies, or hidden trends in big data that humans cannot easily (or at all) detect. The tremendous acceleration frees researchers from tedious tasks and allows them to take the time and effort to think about the data, visualize it and think about it in a conceptual way.

1.2.2 Innovation in the Scientific Approach: Beyond Assistance, a Contribution to Discovery

scientific literature indicates that AI also enables deep changes to the scientific method itself, actively contributing to the process of generating new knowledge. For example, in hypothesis generation, the field of drug discovery is emblematic, as illustrated by Altmann et al. (2018), who describe how AI systems can analyze large bodies of biomedical literature and experimental databases to suggest new research avenues and potential molecules, thus accelerating the discovery cycle. Furthermore, for experimental design and modeling, articles such as those by Gómez-Bombarelli et al. (2018) in materials science demonstrate the use of AI to optimize experimental design by simulating different scenarios and predicting outcomes, significantly reducing the number of trials required. Finally, although ethical questions remain, the literature, notably the discussions around ChatGPT (2022), also explores the capacity of AI to assist researchers in the assisted writing of certain parts of their work, by synthesizing information and improving linguistic clarity, even if human supervision remains crucial to ensure accuracy and originality.

1.2.3 Redefining Roles and Skills: A Necessary Evolution for Researchers

The increasing integration of artificial intelligence into research activities is profoundly transforming the roles and skills of scientists, as highlighted by Larson and King (2020) in their study on the impact of AI on science.

The specialized literature highlights the emergence of new skill profiles, including mastery of data science, databases, and modeling techniques, skills that are now essential to meet the demands of future scientific careers. At the same time, critical thinking and ethical reflection are becoming key, especially for the purpose of deconstructing algorithmically ascribed outcomes and tackling issues of bias, confidentiality and accountability of models, which are all subjects of Crawford (2021) relating to AI and power. Finally, AI advances an increasingly interdisciplinary dynamic to research, where computer scientists, statisticians and specialists from domains must develop close working relationships, as shown in surveys regarding open and collaborative science produced by Nature[1] (2022).
In summary, scientific literature supports the view that AI is an irreversible force for transformation in scientific research. AI will not replace the role of the researcher in research, but it will shift from a researcher's role in interpretation and innovative thought processes to a more high-level thinking and collaborative research approach. To understand and engage in this revolution requires the development of entirely new skills, establishing a robust and rigorous approach to ethics, as well as new ways to work together to access the benefits of AI while also minimizing risks. It is essential to continue to conduct research in this space to help navigate this transition toward a more efficacious and responsible future in science.
These developments illustrate the transformative impact(s) of AI in more than just an analytical tool, but also as a partner in the overall scientific discovery process. Nevertheless, those advances also lead to questions, especially around reliability and ethics, which will be dealt with later.

1.3 Challenges, limitations and boundaries of AI in Research

While AI has created breakthroughs, scientific literature also identifies a few challenges and limitations that necessitate deliberate and considered implementation of these technologies into research. These explicit critiques and assessments of AI in research by various authors addressed ethical, methodological, and technical challenges, calling into question the reliability, fairness, and real autonomy of the AI systems.

1.3.1 Methodological Challenges and the Question of Reliability

One principal concern is the methodological issues posed by AI, particularly with respect to the reliability and reproducibility of results. Critics have raised concerns about transparency in many AI models, particularly complex deep learning architectures, often called "black boxes." According to Castelvecchi (2019), it is challenging to understand why an algorithm made a certain decision, making scientific validation and experiments replication difficult. Transparency for AI algorithms can obscure biases built into the training data. Crawford (2021) and his book called "Atlas of AI" explain that AI often mimics the biases of a society because it is trained on societal data, although this is also the nature of all data extraction. This prevents both ethical and discriminatory results based on societal biases, and erroneous conclusions, particularly in sensitive areas like medicine or the social sciences. Uncertainty also raises questions; while AI can forecast outcomes, the measurement of how confident and how errors are propagated is in its infancy, but this is a necessary step to make sound scientific decisions.

1.3.2 Ethical issues: Responsibility, intellectual property and impact on people

Ethical concerns are crucial to discussions about AI in research. One central issue is liability in the event of an error or incorrect decision made by an AI system. Who is liable if an AI-based medical diagnosis turns out to be wrong, or if an AI-generated hypothesis leads to a costly and unsuccessful experiment? Floridi (2019) and other AI philosophers emphasize the need to establish clear liability frameworks. Intellectual property and attribution are also hot topics. If AI generates scientific text or proposes novel molecular structures, who is the author? The question of originality and scientific authorship is disrupted by the contribution of machines. Finally, the impact on researchers' employment and the very nature of research is a major ethical concern. If AI automates key tasks, could this reduce the need for certain human skills, or conversely, transform the role of the researcher into that of a supervisor of machines? Some authors fear dehumanization of research if critical thinking and human intuition are relegated to the background.

[1] Savona, R., Alberini, C. M., Alessi, L., Baussano, I., Dellaportas, P., Guerra, R., Khozin, S., Modena, A., Pecorelli, S., Rasi, G., Siviero, P. D., & Stein, R. M. (2025). Towards a framework for a new research ecosystem. *Humanities and Social Sciences Communications, 12*(1), Article 1044.
-Ross-Hellauer, T. (2022, 14 mars). Open science, done wrong, will compound inequities. *Nature*, 603(7901).

1.3.3 *T*echnical and Practical Challenges: Cost, Accessibility, and Skills

Despite its transformative potential, the integration of artificial intelligence (AI) into scientific research raises several technical and practical challenges. Another key obstacle is the cost of the infrastructure required to develop and operate AI-based solutions. As Marcus & Davis (2019) discuss, deep learning systems depend on huge computing needs which can only be rendered by institutions with large financial and material resources. This unequal access is further compounded by the fact that the benefits of new advanced technologies are concentrated in a few large companies and a small number of wealthy academic laboratories.
Another basic issue is the skills gap. Using AI in scientific approaches necessitates technical knowledge in programming, data science, and machine learning. However, several reports, including that of the World Economic Forum (2020), note that researchers' current skill set is increasingly out of step with the technology that is coming forward. This situation needs a redesign of academic curricula and provision for continuing education during this development.
Researchers also face challenges with interoperability, data quality, and scaling models. Strubell, et al., (2019) state some of these technical challenges will be even more complicated because they involve collaboration between AI professionals and expertise within the area, and that both approaches are essential to overcoming the highly technical challenges.
Ultimately, inequities in access to digital resources and data, especially in the global south, create inequalities in scientific production while raising the need for open and shared policies as suggested by UNESCO (2021) in its Recommendation on the Ethics of AI.
In conclusion, while AI can be a powerful engine for innovation, the emerging scholarship suggests caution in the approach to the resources and recognition of the limitations of the technologies and ethical and methodological obligations. These issues need to be addressed and resolved, if AI is to serve as a genuine way to progress scientific inquiry in a responsible and equitable manner.

2. Optimizing Research Processes Through AI

Incorporating artificial intelligence (AI) into scientific research is a transformative lever for optimizing processes and changing the way data is collected, processed, and evaluated. AI goes beyond simply automating activities; it increases efficiency and depth of analysis in ways unheard of prior to adopting artificial intelligence, allowing researchers to go beyond traditional means.

2.1 Automation and Data Collection Efficiency

AI is changing the landscape of data collection, and it is doing so faster, more thoroughly, and with less bias and error than humans. Enhanced technologies allow researchers to:
-Leverage intelligent web scraping: AI can scrape vast amounts of online data - scientific articles, databases, social media - automatically, to collect pertinent information. AI can understand the intent of the data, as concepts and context, not simply search terms.
-Analysing data from sensors and connected objects: In fields such as biology, the environment, and engineering, AI processes massive streams of data generated by sensors (meteorological, biometric, industrial) in real time. It identifies patterns, anomalies, and trends that would be impossible to detect manually.
-Facilitating database and literature screening: AI can sift through millions of articles or records to evaluate the ones that are most relevant to your problem and speed up tasks like systematic literature reviews or bibliometrics dramatically.
This can provide researchers with time spent on more valuable and exciting work, including developing hypotheses, designing experiments, and evaluating results instead of finding data.

2.2 Advanced Data Processing and Interpretation

AI's contribution is also crucial in the data processing and interpretation phases, where its ability to handle complexity and volume is unmatched:
- Data Cleaning and Organization: AI excels at detecting and correcting errors, inconsistencies, or duplicates in large data sets. It can standardize formats, impute missing values, and structure unstructured data (text, images, audio), making databases "clean" and ready for analysis.
- Predictive and Prescriptive Analytics: Machine learning algorithms can build models capable of predicting future phenomena (disease progression, material behaviour) or prescribing optimal actions (treatment selection, industrial process optimization).
-Recognition of complex patterns and anomalies: AI, particularly through deep learning, can identify subtle correlations and underlying structures in multi-dimensional data that traditional statistical models or the naked

eye would not be able to detect. This is helpful in identifying new relationships across variables, as well as identifying unusual events earlier.
-Assisted interpretation and data visualization: Though the final interpretation of data will come down to a human, AI can produce intelligent syntheses, automated summaries of key points as well as interactive visualizations. These data/research tools will help researchers to better understand, even with large amounts of data, what the data is communicating to them to better inform decisions.

2.3 Automated interpretation and visualization of results

AI may contribute to research methodology, especially when considering the interpretation and visualization of results, in as much as AI can change the way people interpret and visualize results. As researchers see a large increase in the amount of data they must manage (see above), AI is becoming more important than ever, since it is needed to distil information from data and present it in a way that is understandable.
Historically, researchers have relied on human ingenuity and the use of analytical methods to interpret results. The tools used for analysis alone have a history, and in the past, it was no surprise if the analysis of results never progressed beyond a few tables and charts, often due, in some way, to data complexity. Today, AI, enhanced with machine learning and natural language processing (NLP), can provide intelligent summaries and automated syntheses of research findings and key relationships identified within their datasets to the researcher. For example, a complex simulation may provide an algorithm with thousands of outputs that the algorithm can analyse to identify the parameters with the greatest impact on the results, as well as the key relationships from those parameters, and return structured information to the researcher, or within any research landscape. This will have meaningful application in areas, like genomics or particle physics, where researchers strive to explore datasets that rise to a level of magnitude.
Also, AI has transformed automated data visualization. With AI-driven tools, researchers can create standard graphs and charts but also create interactive and dynamic visualizations that are modified as questions come into play. These systems can identify the best possible types of graphs to visualize specific relationships, expose visual anomalies or further suggest explorations whether from what they "understand" about the data. For example, in bioinformatics, they may visualize complex protein networks or drug molecular interactions in such a way that allows for intuitively gleaning subtle, non-obvious patterns. In the social sciences, a tool could visualize mapping of flows of information across social networks with a granularity and interactivity of exploration that deepens understanding of a given behavioral dynamic.
Nonetheless, it is important to stress that ultimate interpretation is a human responsibility. While AI can provide tremendous capabilities to absorb and share knowledge, it is up to the researcher to add context, use critical judgement, apply prior knowledge, and make decisions. The value of AI is to assist in these processes and lessen the thinking burden of handling and manipulating data to allow scientists to concentrate on generating meaningful information and reporting their findings. Essentially, AI makes interpretation and visualization a much faster, efficient and potentially discoverable process.
In a nutshell, AI serves as an amplifier for the researcher, which enables them to process larger amounts of data and obtain more powerful and expedited conclusions. This all-encompassing optimization of research processes is a significant determinant in expediting scientific discoveries during the digital age.

3. Innovations Brought by AI to the Scientific Process

Artificial Intelligence (AI) is not just refining existing, conventional research procedures; it is transforming the scientific process itself, providing fundamental innovations in how discovery occurs, how knowledge is generated and validated, and how results are reported. These changes represent a paradigm shift in research and science, where AI has shifted from simply being a point of analysis and research tool, to a collaborator in the intellectual process of science.

3.1 Hypothesis Generation by Machine Learning Systems

Hypothesis generation is the center of scientific research, but entails intuition, experience, and the ability of the researcher to integrate independent information. It has been transformed by the advent of machine learning systems, thereby opening the potential to search this space systematically to maximize its possibilities.
Previously, the process of producing a hypothesis was lengthy, but typically constrained by the rapid cognitive processing capacity of the human brain. More recently however, the scale of accumulated scientific data, in almost any form from large genomic databases, scientific publications, experimental results, or even complicated simulations, has surpassed this capacity. As there are simply inadequate hours in the year to learn everything even in the narrowest areas, AI presents as the potential intellectual amplifier.

Machine learning systems, and in particular natural language processing (NLP) and deep learning algorithms, have the capability to read, analyse, and interpret large collections of scientific literature to reveal knowledge gaps, potential contradictions, or unforeseen interactions between isolated concepts. For instance, an AI system might sift through millions of research articles, and through the identification of common themes, patterns, or contextual information suggest possible interactions between proteins, side effects of drugs, or material attributes that have never been tested or even considered by researchers (Altmann et al., 2018). In the realm of drug development this represents a tremendous opportunity. AI-based platforms are now able to screen billions of potential molecules to identify a few that have the greatest probability of being effective against a specific biological target, and forecasting toxicity, affinity and selectivity (Schneider, 2018). Thus, this giant leap from what was formerly taking years of refinement and cost (in the laboratory), can now be done in only a few days or weeks with AI.

This goes beyond mere correlation, where some AI systems may generate explanatory hypotheses. By using logical symbolic reasoning or reinforcement learning processes, AI can construct conceptual models to accounted for an observed phenomenon in a relatively simple model and predict new phenomena. For example, AI-based systems have been most recently developed to generate hypotheses about the mechanisms of cellular aging or the pathways of complex diseases, providing biologists novel lines of investigation (Li et al., 2020). While the hypothesis is generated by machine, it will still require experimental validation by human researchers, although AI-generated hypotheses seed the path to explore and reduce the spatial area of search.

An interesting fringe to this innovates is AI´s ability to find transdisciplinary relationships.

A researcher specializing in physics might not be aware of a relevant discovery in biology that could solve a problem in their field. AI, unconstrained by disciplinary silos, can detect these unexpected connections and suggest hybrid hypotheses that lead to breakthroughs. "Discovery machines" such as "Adam" or "Eve" (King et al., 2009; Williams et al., 2017) are examples of systems capable of generating hypotheses, designing experiments to test them, running these experiments autonomously, and interpreting the results to refine their hypotheses, thus embodying the concept of a "robot scientist."

However, AI-powered hypothesis generation is not without challenges. The explainability of these hypotheses is crucial: if an AI proposes a hypothesis, researchers must be able to understand the underlying reasoning to evaluate and test it. The "black boxes" of some deep models pose a problem in this case. Moreover, there is a risk of "overfitting," where the AI identifies chance correlations in the training data rather than generalizable causal relationships. The quality of the input data is also paramount; biased or incomplete data will lead to biased or poorly relevant hypotheses. Nevertheless, AI represents a major advance, transforming hypothesis generation from an intuitive art to a science of data-augmented discovery.

3.2 Assisted or automated writing of scientific articles

Writing and publishing scientific articles are pillars of scientific communication, but they are often perceived as a burdensome and time-consuming task for researchers. AI is bringing significant innovations to ease this burden, ranging from writing assistance to the near-automatic generation of certain sections of manuscripts.

The goal is not to replace the researcher with a machine writing articles from scratch, but rather to facilitate and accelerate the communication process. AI tools based on natural language processing (NLP), such as large language models (LLM) such as GPT-3, GPT-4, or specialized models in the scientific field, can generate coherent and contextually relevant text.

A key application is assisted writing. Researchers can use AI to:

Generate drafts of standard sections: AI can write introductions by synthesizing relevant literature, methodology sections by describing experimental protocols, or discussion sections by summarizing results and comparing them with previous work (Thorp, 2023). This requires only a few key points or a detailed outline from the user.

Reformulate and improve style: For researchers whose native language is not English, or simply to improve clarity and conciseness, AI can suggest sentence reformulations, correct grammar and spelling, and adapt the style to that required by scientific journals (academically formal, concise, etc.). Tools like Grammarly or DeepL Write, although general, show the potential of this assistance.

Generate abstracts and keywords: AI can analyze the content of a long article to extract its essence and propose a concise and informative abstract, as well as relevant keywords for indexing. This is particularly useful for submissions to conferences or journals.

Create eye-catching headlines: AI can suggest several headline options that summarize the main idea of the article and grab attention.

Beyond assistance, automated writing is beginning to emerge for more specific tasks. "Technical reports" or "preprints" can be generated almost automatically from structured data. For example, a system can analyse a table of experimental results and generate a paragraph describing the observed trends, without direct human intervention (Else & Van Noorden, 2017). This is particularly useful for quickly generating internal reports or documenting routine experiments. Journalist robots already use similar techniques to generate financial or sports reports from structured data.

However, scientific writing by AI raises important ethical and methodological questions. The first is that of originality and authorship. If a significant portion of a text is generated by AI, how should it be attributed? Scientific journals are developing clear policies on this issue, with most requiring that the use of AI be declared and that final responsibility for the content remains with the human authors (Nature, 2023). There is also a risk of accidental plagiarism or producing text that, while grammatically correct, lacks nuance, creativity, or critical thinking. AI models can also "hallucinate" facts or references, creating nonexistent citations or misinformation, requiring rigorous human review.

Despite these challenges, AI has the potential to democratize access to scientific publishing by assisting researchers who are not native speakers of a language or who have less writing experience. It also frees up time for the more creative and conceptual aspects of research by reducing the administrative burden of writing. AI does not replace scientific intellect but complements it by optimizing the process of communicating findings.

3.3 Bias Detection and Improving Scientific Reproducibility

Bias detection and enhancing scientific reproducibility are two vital components of the contemporary scientific process, and AI is emerging as a powerful partner in tackling these chronic problems. The reproducibility crisis in which a vast majority of scientific studies cannot be replicated by any other laboratory has made clear the need for improved tools and methodologies to ensure any fidelity results.

3.3.1 Bias Detection

Bias can occur at myriad levels of the research process, including how a study is designed and how the results are interpreted. AI presents new opportunities to identify and minimize bias:

-Data bias (selection, measurement): AI systems can be trained to examine data and identify any imbalances, outliers, or patterns that could indicate selection or measurement bias. For example, in a medical context, AI can sift through patient records to identify whether certain demographic groups are underrepresented or whether some measurements are systematically incomplete in a way that could bias the outcome of a clinical study (Mehrabi et al., 2021). AI-enabled algorithms can also identify representativeness bias in surveys or text-based quantitative measures in social science.

-Publication bias: AI has the capacity to utilize large databases of scientific publications to evaluate the presence of publication bias. Publication bias is defined as the tendency for positive results to be more likely published than negative or insignificant results. By utilizing larger bundles of literature and showcasing the trends in publication activity, AI can also illustrate a lace or lack of attention to a research area where negative studies were obviously underrepresented (Kiciman et al., 2020).

-Researcher cognitive bias: Although not as overt, AI may also assist in identifying evidence of human cognitive bias in not just the reporting of results, but the interpretations assigned to results. For instance, AI could even offer alternative interpretations of data or observe information that researchers may have missed due to their own confirmation bias. AI could be used in augmented peer review practices that identify critical angles or suggest weaknesses of arguments that human peer reviewers do not perceive.

-Algorithmic bias (self-reflection): It is ironic that AI can be used to determine if it is biased. Models are being developed for fair machine learning (Fair ML) with the intent to develop algorithms that either minimize discrimination or intrinsic bias, and to audit AI (and non-AI) models to reliably determine positionality or bias and suggest corrective changes (Mitchell et al., 2019). This is a general use of AI to make AI more reliable.

3.3.2 Improving Scientific Reproducibility

Reproducibility is the foundation of scientific validity, although achieving reproducibility can be difficult due to complex experiments, poor documentation, and variability in experimental settings. AI provides multiple potential paths to improve reproducibility:

-Automated documentation and rich metadata: AI can automate the recording of metadata about experiments (instrument settings, software versions, environment conditions); this digital lab log could be more detailed and structured, and is crucial during replication (Lamperecht et al., 2020). Connect sensors and AI systems can capture every aspect of an experimental process, providing complete traceability.

-Protocol standardization: AI can analyze and compare experimental protocols to identify differences and then recommend standardizations to facilitate the comparisons and reproducibility of results between laboratories. AI platforms can assist with producing "executable" protocols for use by laboratory robots with minimal variability attributable to the human operator.

-Code and data verification: With computational research, AI can be used to verify the correctness of programming codes and the consistency of datasets. Formal verification and/or static code analysis tools can be used to identify logical errors or discrepancies that would affect the reproducibility of numerical results (Hatton, 2020). AI can also compare datasets and identify differences and would provide assurance that the analyses were performed on the same basis.

-Open Data and Code Discovery: AI has the potential to make it easier to find and access publicly available datasets and programming code, which is crucial for ensuring reproducibility. With AI-driven semantic search engines, we can index and unlock resources that might otherwise be hard to track down.

That said, there are still hurdles to overcome, such as the need for high-quality databases to train these AIs, the challenge of understanding AI-generated results, and some resistance to changing established research practices. Nevertheless, by embracing these AI advancements, the scientific community can work towards a more trustworthy, transparent, and reproducible research environment, ultimately enhancing confidence in scientific findings.

4. Challenges and Limitations of the Use of AI in Research

The growing use of artificial intelligence (AI) is associated with many unprecedented and beneficial developments in scientific research; however, they also provide problems and limitations.

4.1 Lack of transparency ("the black box")

The biggest challenge is the opacity (or "black box") (Castelvecchi, 2019) nature of many AI models, especially if they are complex deep learning architectures. These are difficult, if not impossible, for researchers to understand, to discover how a specific decision and/or prediction is generated. If we struggle to be concretely aware of how an algorithm reasons, we can't scientifically judge (validate) its conclusions, we will not be aware of its errors and we cannot re-create results in other contexts. This lack of transparency affects trust and limits acceptance of AI in areas where interpretability is important, such as forensic medicine or clinical diagnosis.

4.2 Algorithmic Bias and Amplification of Inequalities

AI systems learn from the data they are exposed to, and if that data exhibits bias, is incomplete, or mirrors current societal inequality, the AI is not only likely to reproduce it but may also exaggerate the bias (Crawford, 2021). A simple example would be, an algorithm designed to assist with medical diagnosis from a data set predominantly based on Caucasian patients may not be as accurate or could even be flawed for any patients that do not identify as Caucasian. In research, this can lead to biased findings and discriminatory judgements or exclusion of specific populations or phenomena from further analysis. While bias detection and mitigation of algorithmic bias remain areas of active research (Mehrabi et al., 2021), they remain a significant challenge, because biases can be very subtle and multidimensional.

4.3 Overgeneralization and "hallucinations"

AI models, and especially large language models (LLMs), can occasionally overgeneralize or "hallucinate." In this context, this means they can generate results or text with appearances of plausibility but may be incorrect, inexistent, or factual nonsense (Thorp, 2023). In the research realm, this means creating false hypothesis, creating article summaries with factual errors or even producing citations of non-existent references. In turn, this creates a continual need human surveillance and rigorous validation of any information developed by AI. Therefore, a whole new process of quality control is attached to research now.

4.4 Technological Dependence and Loss of Human Skills

AI may influence a potential over-reliance on technologies assumed to be an adequate substitute. With built-in AI doing certain complex analytical or conceptualization tasks, there is a risk that researchers may start to lose certain basic skills, such as manual statistical analyses, critical thinking when working with raw data, or formulate the basic hypothesis without assistance. This "dishabituation" could leave research vulnerable to failure of AI systems or lack of access to these technologies.

5. Prospects for the Ethical Use of AI in Research

To overcome these challenges, establishing a framework for the ethical and responsible use of AI in research is not only desirable, but imperative.

5.1 AI Ethics Principles Applicable to Research

Several fundamental principles must guide the integration of AI:
• Transparency and explainability: Develop more interpretable AI models ("explainable AI" or XAI) and require clear documentation of the methods and training data used. Researchers must be able to understand how the systems they use work.
• Fairness and non-discrimination: Ensure that the data used to train AI is representative and diverse to avoid reproducing or amplifying biases. Regular audits of AI models are necessary to detect and correct biases.
• Responsibility and accountability: Clearly define the responsibilities of developers, user researchers, and institutions in the event of errors or harm caused by AI. Human researchers will always retain ultimate responsibility for the premises and assertions of their research, even if AI was involved at a preliminary stage.
• Security and reliability: Ensure that support AI systems are both robust (to minimize the potential for errors or vulnerabilities) and that the data is secure and processed in accordance with regulatory requirements related to privacy (e.g., GDPR).
• Confidentiality and data protection: Have sound mechanisms in place to protect sensitive data, especially in areas like health, and obtain informed consent if using a person's data for any AI research purposes.

5.2 Rigorous methodological framework

In addition to general ethical principles, using AI in research rigorously also requires suitable methodological frameworks:
• Standardization and best practices: Develop standardized guidelines and protocols around the use of AI, including documenting algorithms, datasets, training parameters, and results, to make reproducibility and comparability of studies more achievable.
• Human validation and verification: the emphasis should always be that AI is a tool to augment human capability, not a replacement. AI generated hypotheses, analysed results, and written text will always require critical validation and careful verification by human researchers.
• Researcher training: Incorporate data science, AI ethics, and critical thinking about autonomous systems into university curricula and researcher continuing education. Scientists must be educated on the capabilities and limitations of AI.
• Interdisciplinary collaboration: AI experts, scientific specialists, and ethicists should collaborate on designing, developing, and deploying AI systems that meet research specific requirements while being cognizant of ethical obligations.
• Publication policies: Publishers and scientific journals should have disclosed policies for the use of AI in article submissions, requiring that authors disclose the use of AI and that authors retain full accountability.

5.3 Career prospects

With respect to research, the future of AI is bright if ethically motivated and methodologically grounded challenges are addressed:
• Ethics by Design: Ensure the ethical aspects of AI development are included in the design phase, and not as an afterthought.
• Development of Causal AI: Move beyond simple correlation to AI being able to organize data into causal relationships, which will provide considerably stronger scientific merit for discoveries.
• Regulatory Frameworks: Strengthen appropriate national and international policies governing the use of AI in research, balance protections for individuals, and encourage innovation in research.
• Public Literacy on AI: Educate the public about what AI can and cannot do research, will help maintain public trust in AI-aided science.

RECOMMENDATION

The encroachment of artificial intelligence (AI) into scientific research is an unavoidable, perhaps even unprecedented, revolution that invites a wealth of new opportunities. However, to harness those opportunities and avoid diminishing returns, a thoughtful, forward-looking, and concerted approach must be adopted.

To build trust and reliability with the use of AI whatever the output, it is imperative to improve model transparency and explainability. Hopefully, we will eventually embark on more interpretable AI (XAI) models that will enable researchers to comprehend the rationales of the algorithms to qualify their results. Thorough documentation, covering everything from training data through hyperparameters and architectures implemented, is also vital for reproducible research endeavours. To the greatest extent possible - and while respecting confidentiality - it should be strongly advocated, promoted, and rewarded to publish codes and datasets to facilitate peer review and reanalysis.
Specific attention should be paid to intervening bias in algorithms that can perpetuate inequities and shape the conclusions of the research. Systematic audits of the data sources upstream can provide opportunities for revealing and rectifying representation biases and help to create "fair" AI (Fair ML) that reduces discrimination. It is also critical that researchers are aware of possible sources of bias so that an informed approach can be taken to interrogate AI-generated output. Since AI is an augmentation tool and not a replacement for human intelligence, it is vital that human validation is considered very robust. All AI-generated outputs including hypotheses, summaries, and references require a systematic review by subject-matter experts in order to minimize "hallucinations" and misrepresentations. It is paramount that researchers retain and develop their analytical capabilities and critical thinking which limits over-reliance on technology.
In addition to promoting best practice for AI use, clear ethical and regulatory frameworks are essential to responsible AI use. Examples of frameworks include clarifying roles and responsibilities when mistakes are made with algorithms, updating scientific journal publication policies to compel disclosure of AI use, identifying intellectual property matters and ensuring AI is secured and sensitive data is kept confidential.
Finally, a serious commitment by funding agencies will be required to train and educate the workforce in preparation for the AI era. University programs and curricula must feature modules on AI, data sciences, and ethics of AI. Significant investments will enable universities to support partnerships of AI experts, scientific experts, ethical experts, and develop and use AI for real scientific problems, following thorough ethics guidelines. If the science and technology ecosystem embrace and adopts these recommendations, the scientific community will surely realize the revolutionary advantages of AI, while also ensuring the discoveries of the future will not only be novel, but reliable, equitable, and beneficial for society.

CONCLUSION

The rise of artificial intelligence (AI) gives us a milestone in the design, execution, and communication of scientific research. AI is much more than technology: it is a vector of systemic innovation that has a radical impact on the methodological dimensions of contemporary science. At this point in history, it is a disruptive and transformational force in the scientific process, facilitating the automation of massive data collection; complex statistics; intelligent visualization of results; predictive interpretation; and even hypothesis generation.
On the one hand, AI allows a substantial acceleration of preliminary approaches, due to algorithms that can identify non-trivial correlations in large data sets. Technologies, particularly deep learning, have shown their usefulness in fields as varied as genomics, astrophysics, and computational social sciences. On the other hand, AI is assisting in the reinvention of the scientific process itself. For instance, it can assist in the generation of hypotheses through the automatic analysis of scientific corpora (Altmann et al., 2018); optimize experimentation protocols (Gómez-Bombarelli et al., 2018); or support the writing of scientific articles using natural language processing technologies like ChatGPT or SciNote.
However, this methodological revolution is rife with risk and limitations. Criticism revolves around several main points. The first will be the opaqueness of algorithms or "black boxes," which causes issues of scientific transparency and the ability to trace automated reasoning (Marcus & Davis, 2019). In addition, algorithmic biases in data or models can bias result and reproduce inequities and issues of ethics or epistemic justice (Crawford, 2021). Also, there is the risk of generative hallucinations, or inaccurate or fictitious results, and the danger of over-reliance on automated systems, which may lead to a diminished capacity on the part of researchers to maintain certain critical skills.
Faced with similarly serious challenges, a commitment to ethical, rigorous, and reflexive aspects of AI and its integration into research is fundamentally important. It is not merely adopting these technologies but framing the issues with some principles and responsible practices. The recently published papers offer several recommendations: demanding further explainability of AI models, implementation of algorithm audits for instances of bias with corrective actions, making human validation of AI-generated outcomes a virtually systematic precautionary step, and developing adequate regulation with clarity on duties and obligations, intellectual property rights, and transparency of methods.

Moreover, it is important to provide the opportunity for researchers to learn and train on AI related tools and to engage with acquiring skills related to data science and digital ethics and to foster interdisciplinary collaborations with computer scientists, statisticians, philosophers, etc. as well as disciplinary professionals to co-construct augmented but controlled research.

Fundamentally, AI does not intend to literally replace human thinking nor the judgment of scientists. AI is instead a source of cognitive amplification, enhancing capabilities for analysis, modelling, and knowledge creation. Together, human and artificial intelligence are presenting an extraordinary prospect to address our greatest challenges, be they health, environmental, technological, or social. It is through judiciousness, appropriateness, and responsibility that the scientific community can be assured that future discoveries will not just be rapid and clever but also fair, trustworthy, and for the common good.

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