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Editorial

Artificial Intelligence and technological and scientific research

Inteligência Artificial e as pesquisas científicas e tecnológicas

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Artificial Intelligence (AI) has profoundly transformed health research, offering unprecedented benefits.[1] Understanding the different types of machine learning used in scientific and technological research — as well as their specific characteristics and risks — is essential for responsible and effective use. **Supervised learning** relies on data previously validated by experts and has been widely applied in automated diagnostics and clinical outcome prediction, for example. **Unsupervised learning** is used to detect patterns and structures in raw data, making it useful for exploring unknown relationships or generating innovative hypotheses, while **reinforcement learning** simulates interactive decision-making processes, with potential applications in areas such as optimizing personalized treatments.

While much of AI's application in scientific research focuses on the analysis of structured data—such as clinical, epidemiological, and laboratory studies—another significant field involves the so-called Large Language Models (LLMs), like ChatGPT or Claude (developed by Anthropic). These models operate with billions of parameters trained on vast textual datasets and are examples of **self-supervised machine learning**, in which the text itself serves as both input and output during training. In other words, the model learns to predict the next word or sequence of words based on the preceding context, without requiring human validation (i.e., manually assigned labels by experts to indicate the correct answer, as is the case in supervised learning). Although this approach enables the development of highly versatile systems, it also presents challenges such as the generation of inaccurate or unrealistic information, a phenomenon known as hallucination. Using these systems demands critical analysis, human verification, and a clear understanding of their limitations. For more attentive users, these limitations can become opportunities: they require meticulous verification of sources and information, encourage active pursuit of knowledge and evidence, and foster critical thinking skills grounded in reliability and scientific rigor.

Supervised models rely on previously validated data, and their accuracy depends on the quality and diversity of that information. Unsupervised models, due to their exploratory nature, uncover patterns that require expert validation to ensure scientific robustness. The choice of AI model should consider the research objective, the quality of the data, and the level of validation required, reinforcing the importance of audited and expert-validated datasets to ensure that models remain reliable and applicable to clinical practice.

Among the many applications in scientific research, AI tools stand out for their ability to assist in protocol development, literature review, identification of gaps in scientific knowledge, and even in experimental design, such as the verification of new hypotheses. For example, algorithms can analyze large genomic databases, medical imaging, or rapidly detect correlations between treatments, diagnoses, costs, and prognoses derived from electronic health records.[1] This capability is strategic for accelerating the discovery of biomarkers, the identification of therapeutic targets, and the analysis of epidemiological patterns. Moreover, it expands opportunities for young researchers, especially those from regions with limited infrastructure, who can access cloud-based computing environments or pre-trained models, allowing them to engage productively in scientific research from the early stages of their careers and contribute to greater diversity in knowledge production spaces.

Another advantage of AI is its ability to analyze large volumes of data (big data) with high-speed, large-scale processing, enabling the overcoming of longstanding challenges, from identifying complex interactions in trials involving thousands of individuals to monitoring trends in real time. In contexts such as pandemics, genetics, and population health, this capability allows for rapid and precise responses.

However, these advances are not exempt from significant challenges and risks that must be acknowledged. One such issue is the lack of energy sustainability. Processing complex models, such as LLMs or deep learning networks, requires enormous energy consumption and results in high carbon emissions, a particularly concerning problem in emerging countries, where costs may hinder large-scale adoption. Another critical point involves the cognitive and formative development of researchers. Overreliance on AI, especially among young scientists, can lead to mental accommodation, shortening the gradual learning process by skipping fundamental steps such as critical and in-depth reading, reflection on evidence, and engagement with diverse perspectives. This may compromise the development of strong analytical skills, reducing the researcher's ability to rigorously evaluate information and construct well-founded interpretations. Accelerating intellectual maturation and impoverishing critical thinking capacity are likely consequences.

For researchers with limited experience and academic background, the tendency of generative models like LLMs to produce superficial or inaccurate descriptions poses an additional challenge. Without a solid foundation to identify inconsistencies, there is a risk of absorbing and reproducing misleading information, which can compromise the quality of scientific output.

From this perspective, Aaron French[2] provocatively asks: “Is ChatGPT making us stupid?” He argues that by delegating cognitive tasks to AI, we risk weakening our ability to think critically, solve complex problems, and engage deeply with knowledge. French highlights the Dunning-Kruger effect, in which individuals tend to overestimate their competence due to a lack of awareness of their limitations. This can lead to a false sense of understanding and, without proper reflection, result in artificial self-confidence while impoverishing cognition. On the other hand, Samantha Green, writing for Scholarly Kitchen, suggests that fear surrounding AI can actually drive learning and innovation. She emphasizes that informed skepticism is an opportunity to lead with ethics and strategy, helping shape the future of technology in a responsible and thoughtful way.

As a matter of fact, the critical and reflective use of AI, especially in the context of scientific research, can enhance human intelligence by generating ideas, stimulating curiosity, and deepening discussions. However, it should be seen as a starting point, not the end of a long intellectual process.

A culture of responsible and ethical use, with critical validation of automated results, demands solid argumentation, free from shortcuts, and must avoid algorithmic bias, discrimination, or intellectual complacency. The future of AI in scientific research points toward an increasingly deep integration between data science, bioinformatics, and clinical practice. Emerging trends include the use of multimodal models capable of correlating clinical, genomic, and environmental data. The advancement of Explainable AI, which seeks to improve the transparency and interpretability of algorithms, and the strengthening of ethical and regulatory frameworks are essential to ensure security, privacy, and equity in the use of these technologies. As AI becomes more accessible and specialized, it is expected not only to accelerate scientific discoveries, but also to personalize prevention and prediction strategies. However, the success of this trajectory will depend on investments in researchers' critical training, sustainable infrastructure, and a collaborative global governance capable of balancing innovation with social responsibility.

AI innovations also include the fine-tuning of foundational models using specialized clinical datasets, thereby promoting greater safety and accuracy in automated responses, the use of generative AI for rapid synthesis of scientific evidence, integration with wearable devices and Medical Internet of Things (IoMT) systems, enabling real-time data studies, and the application of AI in identifying and reducing health disparities.

Additionally, there is growing interest in hybrid models that combine symbolic reasoning with statistical learning, bringing AI closer to human clinical reasoning. These innovations reinforce that the future of AI in science will be both technical and ethical, requiring a commitment to quality, justice, and transparency.

Among emerging trends, the vision of Eric Topol, presented in a lecture for the National Institutes of Health,[5] stands out as he argues that AI is not merely a tool for data analysis, but a means to restore humanity to medicine, freeing professionals from administrative burdens, reducing burnout, and enhancing clinical connection with patients, thereby transforming healthcare delivery. According to Topol,[5] the advancement of AI also challenges traditional methodological paradigms, demanding approaches capable of integrating unstructured data and dynamic forms of data collection and analysis, while simultaneously redefining how scientific knowledge is investigated, systematized, and applied.[5]

Increasingly, deep learning algorithms are being employed to uncover complex correlations and patterns within heterogeneous databases, enabling the formulation of innovative hypotheses based on robust empirical evidence. Moreover, by expanding access to cutting-edge analytical tools, AI contributes to the democratization of translational research, allowing institutions with limited technological infrastructure to participate in collaborative, multicenter studies. In this context, the role of AI goes beyond accelerating analysis—it redefines how scientific knowledge is investigated, systematized, and applied, provided it is accompanied by an ethical commitment to quality, transparency, and equity in the production of health-related knowledge.[5]

Another significant development is the growing emphasis on transparency and traceability in AI model development, including detailed documentation of training data, model versions, and validation criteria —practices known as model cards and transparency statements — which strengthen scientific reproducibility. Furthermore, there is increasing recognition of the need for multisectoral governance, involving not only technical experts and healthcare professionals, but also patients, regulators, and policymakers. This inclusive approach ensures that AI solutions address real-world needs, maintain public trust, and preserve ethical and practical relevance.[6]

Ultimately, AI holds extraordinary potential to accelerate and democratize knowledge production, but the key to success lies in how these tools are used. Treating AI-generated responses as a starting point rather than a final answer requires intellectual discipline, critical thinking, and ethical responsibility. This is the essence of enhancing human intelligence, not replacing it.

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