Artificial Intelligence in Scientific Research: Lessons for SPIs

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Abstract

Rapid advancements in artificial intelligence (AI) pose challenging questions for science-policy interfaces (SPIs). One rapidly growing application of AI is in scientific research in the life sciences, chemistry, and related fields. We reviewed empirical evidence on the benefits and risks SPIs face due to the increasing use of AI in science and highlighted potential policy interventions to ensure this technology's transformative yet responsible use. On the one hand, AI tools may enhance the accuracy of ongoing scientific research, supporting SPIs by facilitating improved evidence-based policymaking. On the other hand, biases or inaccuracies in input data to AI tools, among other risks, may lead to ineffective SPI decision-making. To combat these challenges, policymakers, scientists, and other institutions should adopt a two-pronged strategy focused on both enhancing the positive uses of AI in science and addressing potential shortcomings.

The advancement of artificial intelligence (AI), exemplified by the rise of ChatGPT and other generative AI tools, is likely to rapidly impact global economics, politics, and other domains, with scientific research being no exception (Sætra, 2023). Across fields such as biology, chemistry, and more, AI tools may soon enable more rapid, transformative, and accurate scientific research that may produce more accurate findings and promote improved evidence-based decision-making by firms and governments. However, risks such as bias in input data may hinder the benefits that the use of AI tools in scientific research offers to science-policy interfaces (SPIs). Given the rapid nature of new developments in AI and the urgency of setting proper guidelines for these tools' use, we qualitatively reviewed current literature on the use of AI tools in science to identify best practices to maximize these tools' benefits while minimizing their risk.

Potential benefits from the use of AI in science

A wide variety of artificial intelligence tools are being deployed across scientific research. Their applications have been used across many scientific disciplines and throughout multiple stages of the traditional scientific method, with increased use of these tools being even more likely in the future. Indeed, as per a recent survey in *Nature*, of sampled researchers who currently use AI, nearly 47% said AI would be very useful in their field in the future, while an additional share of more than 25% said AI would be essential to their field in the future (Van Noorden & Perkel, 2023).

From the standpoint of SPIs, the increasing use of AI tools offers immense promise in several ways, of which we isolate three. First, novel AI tools may directly lead to improved scientific findings, which, in turn, may lead to better evidence-based policymaking. Across a wide variety of fields, AI tools may have useful direct applications in research. In the life sciences, for example, AlphaFold enables researchers to effectively predict the structures of proteins (Perrakis & Sixma, 2021). Autoencoder AI models enable material scientists to identify potential compounds with desirable properties (Vasylenko et al., 2021). In environmental science, AI tools like Google DeepMind's GraphCast display promise in predicting weather patterns, while other tools may one day better model the potential impacts of climate change (Schultz et al., 2021; Schneider et al., 2023; Lam et al., 2023). These examples are non-exhaustive but speak to the potentially transformative role that the direct use of AI in scientific research will have.

If these new AI tools produce novel and more comprehensive findings than researchers could previously, the result will facilitate better evidence-based policymaking by firms and governments. For example, if AI tools are able to predict the localized impacts of climate change more accurately, governments could use these projections to inform better evidence-based policy on how to mitigate the harms local populations face due to climatic events (Cowls et al., 2023). In this way, the direct use of AI in science will not only directly lead to better research but may permit more accurate policymaking based on that research.

Second, AI tools may aid SPIs by potentially enabling researchers to achieve greater general scientific productivity. In addition to being directly used in modeling or screening, AI tools may support scientists through the research process. For example, in the aforementioned *Nature* survey, more than 30% of scientists said that AI currently had major benefits in summarizing existing scientific literature, brainstorming, and facilitating coding for researchers (Van Noorden & Perkel, 2023). Further evidence even suggests that AI tools may also be useful in the writing of scientific manuscripts (Altmaë et al., 2023). Together, these AI tools may enable researchers to more efficiently review literature and conduct analyses, potentially increasing the pace of vital scientific progress that could lead to more lifesaving therapeutics, more useful electronic materials, and more (Agrawal et al., 2019). From a policymaking and strategy standpoint, general increases in scientific productivity will yield a wider array of scientific evidence that policymakers and firm decision-makers can use to make evidence-based decisions.

Third, AI tools may offer benefits as a tool for democratizing science globally. Empirical evidence suggests one of the most common uses of AI in science today is in aiding scientists who lack fluency in international scientific languages such as English (Van Noorden & Perkel, 2023). According to the aforementioned *Nature* survey, more than 50% of scientists believe current AI tools can aid researchers who do not speak English as a first language with translation, summarizing, and editing scientific articles (Van Noorden & Perkel, 2023). Past evidence suggests non-English speaking researchers in science share their ideas less frequently at conferences, limiting their ability to share what may be transformative ideas with the global scientific community (Amano et al., 2023). Furthermore, in some fields like biodiversity, for example, evidence suggests non-English documents comprise more than 30% of literature in those fields, meaning language barriers may limit the dissemination of valuable scientific ideas (Amano et al., 2016). Thus, the translational application of AI tools may be very useful to democratize global science across language barriers, potentially leading to more global collaboration and improved exchanges of ideas that can bolster scientific progress.

These three benefits are not exhaustive — AI tools are likely to offer a much larger variety of benefits to researchers — but serve to highlight the powerful benefits of increasing the use of AI in science.

Risks to SPIs from the use of AI in science

AI tools in science, however, are not without significant risks for SPIs as well. First, there is a significant risk of bias in AI tools. If datasets used as input or training data for AI models omit certain populations, regions, or other groups, AI tools may produce findings that are inaccurate and may reify structural biases (Hanson et al., 2023). For example, some researchers suggest that because AI models that predict the risk of cardiovascular disease are trained on majority-male datasets, there is a risk that the outputs of these AI models may be biased to be less accurate in women (Norori et al., 2021). If policymakers used the results of biased AI models to inform evidence-based decisions, the resulting policies may likely magnify the biases present in the AI model, resulting in poorly designed or even harmful interventions (Hanson et al., 2023).

Second, current guidelines for the use of AI in scientific research face significant reproducibility issues due to inconsistencies in how scientists detail their use of AI methods in their scientific papers (Ball, 2023). One study sampling 255 scientific papers found that more than 30% lacked reproducibility due to unclear notation, missing algorithm details, and more (Raff, 2019). Reproducibility issues remain problematic because they prevent other scientists from providing additional verification to support the conclusions of initial studies, preventing the development of robust evidence (Begley et al., 2015). In turn, for governments, reproducibility issues mean policymakers cannot be as confident in the veracity of the scientific evidence they may use to inform their decisions, leading to potentially less accurate interventions or disincentivizing policymakers from relying on as much scientific evidence.

These risks — and many others — should be taken seriously by SPIs. If scientific research with AI tools leads to ineffective or even harmful policy decisions, the result may fuel broader hesitancy among policymakers against using of the results of research that uses AI methods to inform evidence-based policy. In addition, ineffective policies may also lead to broader public backlash against trusting studies that use AI tools in research, potentially furthering distrust in science in the wake of a pandemic where trust in science has already dropped steadily worldwide (Ishmael-Perkins et al., 2023). In particular, if biases in AI tools inform policy interventions, which then are harmful to marginalized communities, the result would only build on lingering distrust towards governments in these communities and limit global inclusion efforts (Ishmael-Perkins et al., 2023).

Policy recommendations

Given the benefits and risks, SPIs should adopt a two-pronged strategy centered around maximizing the benefits of AI in science while minimizing its harms. First, governments should promote educational programs to train a new generation of scientists more familiar with AI tools and increase funding for the use of AI tools in science. Empirical evidence suggests that significant numbers of scientists indicate that a lack of sufficient AI talent and funding limitations are both major hurdles limiting the positive uses of AI in science (Van Noorden & Perkel, 2023). Thus, these policy efforts by governments would be a useful step to tackle this issue. Public-private partnerships with firms, foundations, and other entities as part of efforts to promote the use of AI in science may be helpful (Baldoni et al., 2020).

Second, national and international scientific bodies should convene to set discipline-wide guidelines and checklists on the use of AI in scientific research, following the example of the recent six-point framework set by the American Geological Union (AGU), which includes scientists from 100 countries (Hanson et al., 2023). Field-wide guidelines can serve to limit the use of biased input or training data that may lead to inaccurate outputs from AI models (Hanson et al., 2023). Meanwhile, guidelines on disclosure practices similar to those proposed in the life sciences could help ensure a greater share of papers disclose sufficient information to be reproducible by other researchers, building confidence in these studies' findings (Heil et al., 2021).

Third and lastly, policymakers should increase the number of scientists involved in policymaking processes. Increasing the number of scientists present in the policymaking process may allow these domain-specific experts to assess the quality of evidence emerging from AI tools that may be cited or used in policymaking decisions. This input could happen through external technical advisory panels, formal inclusion, or other processes, but this input is vital to ensure evidence from AI-generated tools is correctly assessed to inform policy.

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