

VIEWPOINT

Avoiding bias in artificial intelligence

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Abstract

Artificial intelligence (AI) is ubiquitous and expanding, and the healthcare industry has rapidly adopted AI and machine learning for numerous applications. It is essential to understand that AI is not immune to the biases that impact our clinical and academic work, and in fact may inadvertently amplify rather than reduce them. As we harness the power of AI, it is our obligation to our patients to ensure that we address these concerns. We must take responsibility for proactive stewardship to protect against bias, not only for new AI algorithms, but also for our research studies that may one day provide data for those algorithms.

KEYWORDS

evidence-based medicine, imaging, medical therapy of chronic rhinosinusitis, patient-reported outcome measure, quality of life, simulation training, statistics

Artificial intelligence (AI) is ubiquitous and expanding rapidly. Behind the scenes of everything from routine grocery shopping to our daily commutes, complex algorithms are furiously at work, collecting and analyzing immense quantities of data to optimize workflows, predict behaviors, profile users, and monetize consumer activity. Healthcare is the largest and fastest growing industry in the United States, representing over \$4 trillion annually and about 20% of the US Gross Domestic Product.¹ Healthcare companies, including hospital, insurance, and pharmaceutical conglomerates, among others, have been quick to adopt AI as they seek to maximize revenue. Medical researchers and clinicians, too, have recognized the value of algorithmic data collection and machine learning, and have utilized these tools for histopathology, radiology, epidemiology, genetics, and numerous other applications.

It is tempting to regard the information collected with AI as improved and objective data, free from the human biases that often cloud our clinical and academic work—selection bias, confirmation bias, demographic bias, and

others. Yet it is essential to understand that AI algorithms are not immune to these pervasive biases, and in fact may inadvertently amplify rather than reduce them. As a community of Rhinology researchers and clinicians, we must proactively identify and address these concerns as we embrace these powerful new tools, before such biases become embedded in massive datasets. What we get out of automated computer algorithms will only be as good as what we put in, and the current body of Rhinology data has ample room for improvement.

The history of AI is one of remarkable intellectual feats, yet also one of unintentionally amplified biases. In the 1970s, St. George's Hospital Medical School in London developed a computer program to screen medical school applications. In 1986, the school was found guilty of racial and sexual discrimination by the British Commission for Racial Equality when it was discovered that the program had inadvertently screened out women and people whose names sounded foreign.² Their program did not invent the biases; in fact, it was written specifically to correlate to the

historic preferences of the selection panel. The output of the machine learning amplified the input of the preexisting human biases, while also exposing those underlying biases that may have otherwise been difficult to quantify. In Broward County, Florida, the criminal court system, like many others across the country, utilized an AI algorithm to assist in determining jail sentences of convicts by scoring defendants on their likelihood of committing future crimes. When independent journalists retrospectively analyzed the results, they determined that after controlling for defendants' criminal history, prior recidivism, age, and gender, Black defendants were 77% more likely than White defendants to be scored as high risk of committing a future violent crime.³

Does bias in AI impact our patients? The journal *Science* published a remarkable study in 2019 in which investigators used a large dataset to explore an algorithm regularly utilized by large healthcare systems and insurance companies to target patients for "high-risk care management." The algorithm, representing one of the largest commercial risk-prediction tools, is applied to roughly 200 million people in the United States each year. Such algorithms are common in the healthcare industry to optimize cost efficiency, as certain patients are more likely to have complex health needs and are thus provided additional financial and logistical support, including healthcare providers and improved access to other scarce resources. The investigators found that at the same level of algorithm-predicted risk, Black patients have significantly more illness burden than White patients.⁴ In other words, the algorithms applied to the majority of Americans each year appear to allocate more resources for White patients than Black patients with the same level of illness. The complexity of these stories may keep them from becoming headline news, but the biases in these powerful tools impact millions of real lives.

Collectively, our clinical data in Rhinology suffers from several limitations and biases that could similarly become amplified by AI if we are not careful. A systematic review of prospective chronic rhinosinusitis (CRS) studies in the United States, encompassing over 12,000 patients, demonstrated that every demographic and ethnic minority was significantly underrepresented relative to its portion of the population (and probably relative to its share of CRS patients).⁵ Separate analyses of prospective clinical trials studying CRS and rhinitis through the National Institute of Health and the US Food and Drug Administration have also found that women and minorities are routinely underrepresented.^{6–8} It is not hard to imagine a scenario where insurance companies utilize input from these biased data sets to create an algorithm to determine risk of disease progression, for example, and disproportionately deny sinus surgery coverage for women or minorities based

on a skewed interpretation of responses to nonsurgical therapy.

Furthermore, for rhinologic malignancies, patients of minority demographic groups and lower socioeconomic status appear more likely to present with advanced stage disease.^{9–12} Considering that such disorders are quite rare at baseline, this disparity suggests that as a specialty, our collective datasets lack proportionally representative demographic minority patients with early-stage cancer. What would these data yield when used as input for a machine-learning algorithm programmed to screen radiology studies or histopathology of biopsies for, say, malignant conversion of inverted papilloma? Could we inadvertently train that algorithm to conclude that early-stage malignancy simply does not occur in minority demographic groups? Could that algorithm process all available data points—patient age, symptoms, demographic profile, etc.—and erroneously score the histopathology of a minority patient's biopsy as low risk, simply because we unintentionally taught the algorithm that minority patients are at disproportionately low risk for early-stage malignancy?

Even more concerning would be a machine learning algorithm determining the best treatment pathways for patients with sinonasal cancer based on known survival rates, with a goal of sparing patients aggressive treatments that do not extend survival. Unfortunately, demographic disparities in sinonasal cancer survival are not only due to differences in cancer stage at presentation, but also because of disparities in which demographic groups undergo multimodal treatment, the standard of care.^{9,13} Any machine learning based on these disparities is condemned to replicate and amplify those biases.

Fortunately, there are ways to minimize the risk of bias in machine learning and AI. First, we must identify potential sources of such biases, as recent Rhinology literature has begun to do. Next, we must identify accurate and representative data, which may require the initial use of "supervised" AI models whereby investigators directly control the input data for machine learning. Furthermore, transparency and access to these models allow scientific peers to examine algorithms for bias. And last, investigators must be vigilant in continuous assessment of data used for training and algorithm results. Not only will these efforts benefit our patients, but they may also be required, as our regulatory bodies have already begun to consider some clinical decision support software as medical devices, subject to specific approval.¹⁴

These issues are as urgent as they are complex. AI in medicine has immense potential to transform the way we deliver care and improve the lives of countless patients. Yet it is essential that we recognize the prevalence of human biases and the risks of propagating and

amplifying these limitations with machine learning. As we harness the power of AI, it is our obligation to our patients to ensure that we address these concerns. We must take responsibility for proactive stewardship to protect against bias, not only for new AI algorithms, but also for our research studies that may one day provide data for those algorithms.

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CONFLICTS OF INTEREST

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