VIEWPOINT

# What This Computer Needs Is a Physician
## Humanism and Artificial Intelligence

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**The nationwide implementation** of electronic medical records (EMRs) resulted in many unanticipated consequences, even as these systems enabled most of a patient's data to be gathered in one place and made those data readily accessible to clinicians caring for that patient. The redundancy of the notes, the burden of alerts, and the overflowing inbox has led to the "4000 keystroke a day" problem[1] and has contributed to, and perhaps even accelerated, physician reports of symptoms of burnout. Even though the EMR may serve as an efficient administrative business and billing tool, and even as a powerful research warehouse for clinical data, most EMRs serve their frontline users quite poorly. The unanticipated consequences include the loss of important social rituals (between physicians and between physicians and nurses and other health care workers) around the chart rack and in the radiology suite, where all specialties converged to discuss patients.

The lessons learned with the EMR should serve as a guide as artificial intelligence and machine learning are developed to help process and creatively use the vast amounts of data being generated in the health care system. Outside of medicine, the use of artificial intelligence in predictive policing, bail decisions, and credit scoring has shown that artificial intelligence can actually exaggerate racial and other bias. For example, a program used for risk assessment by US courts mistakenly flagged black prisoners as likely to offend at twice the rate it mistakenly flagged white prisoners.[2]

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Similar concerns around artificial intelligence predictive models in health care have been discussed: clearly, in the 3-step process of selecting a dataset, creating an appropriate predictive model, and evaluating and refining the model, there is nothing more critical than the data. Bad data (such as from the EMR) can be amplified into worse models. For example, a model might classify patients with a history of asthma who present with pneumonia as having a lower risk of mortality than those with pneumonia alone,[3] not registering the context that this is an artifact of clinicians admitting and treating such patients earlier and more aggressively. Since machine learning presents no human interface and cannot be interrogated, even if its predictions are extraordinarily accurate, some clinicians are likely to view the "black box" with suspicion.

The missing piece in the dialectic around artificial intelligence and machine learning in health care is understanding the key step of separating prediction from action and recommendation. Such separation of prediction from action and recommendation requires a change in how clinicians think about using models developed using machine learning. In 2001, the statistician Breiman[4] suggested the need to move away from the culture of assuming that models that are not causal and cannot explain the underlying process are useless. Instead, clinicians should seek a partnership in which the machine predicts (at a demonstrably higher accuracy), and the human explains and decides on action. The same sentiment was expressed by Califf and Rosati as early as 1981 in an editorial on predictive risk factors emerging from a computer database on exercise testing for coronary artery disease: "Proper interpretation and use of computerized data will depend as much on wise doctors as any other source of data in the past."[5]

The 2 cultures—computer and the physician—must work together. For example, clinicians are biased toward optimistic prediction, often overestimating life expectancy by a factor of 5, while predictive models trained from vast amounts of data do better; using these well-calibrated probability estimates of an outcome, clinicians can then can act appropriately for patients at the highest risk.[6] The lead time a predictive model can offer to allow for an alternative action matters a great deal. Well-calibrated levels of risk for each outcome, and the timely execution of an alternative action, are needed for a model to be useful. In short, a black-box model can lead physicians to good decisions but only if they keep human intelligence in the loop, bringing in the societal, clinical, and personal context. Additionally, the unique human brain and clinical training can generate new ideas, see new applications and uses of artificial intelligence and machine learning, and connect these technologies to the humanities and the social sciences in ways that current computers do not.

The ability of artificial intelligence to automate and help in the clerical functions (such as servicing the EMR) that now take up so much of a clinician's time would also be welcome. Although not currently accurate enough, automated charting using speech recognition during a patient visit would be valuable and could free clinicians to return to facing the patient rather than spending almost twice as much time on the "iPatient"—the patient file in the EMR.[7] More time for human-to-patient interaction might both improve care and allow physicians to record, and accurately register, more phenotypes[8] and more nuance. Better diagnosis, and diagnostic algorithms providing more

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accurate differential diagnoses, might reshape the traditional CPC (clinical problem solving) exercise, just as the development of imaging modalities and sophisticated laboratory testing made the autopsy less relevant.

As with the EMR, there are legitimate concerns that artificial intelligence applications might jeopardize critical social interactions between colleagues and with the patient, affecting the lived experiences of both groups. But concerns about physician "unemployment" and "de-skilling" are overblown.[9] In the same manner that automated blood pressure measurement and automated blood cell counts freed clinicians from some tasks, artificial intelligence could bring back meaning and purpose in the practice of medicine while providing new levels of efficiency and accuracy. Physicians must proactively guide, oversee, and monitor the adoption of artificial intelligence as a partner in patient care.

In the care of the sick, there is a key function played by physicians, referred to by Tinsley Harrison as the "priestly function of the physician." Human intelligence working with artificial intelligence—a well-informed, empathetic clinician armed with good predictive tools and unburdened from clerical drudgery—can bring physicians closer to fulfilling Peabody's maxim that the secret of care is in "caring for the patient."

## ARTICLE INFORMATION

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