

VIEWPOINT

Artificial Intelligence in Health Care

Will the Value Match the Hype?

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Artificial intelligence (AI) and its many related applications (ie, big data, deep analytics, machine learning) have entered medicine's "magic bullet" phase. Desperate for a solution for the never-ending challenges of cost, quality, equity, and access, a steady stream of books, articles, and corporate pronouncements makes it seem like health care is on the cusp of an "AI revolution," one that will finally result in high-value care.

While AI has been responsible for some stunning advances, particularly in the area of visual pattern recognition,¹⁻³ a major challenge will be in converting AI-derived predictions or recommendations into effective action.

The most pressing problem with the US health care system is not a lack of data or analytics but changing the behavior of millions of patients and clinicians. Physician behaviors, including ordering tests, procedures, pharmaceuticals, and other treatments, are responsible for 80% of health care costs. Similarly, patient behaviors, including eating well, exercising, not smoking, moderate alcohol consumption, and medication adherence, influence more than half of the development of and outcomes related to chronic diseases. A narrow focus on data and analytics will distract the health system from what is needed to achieve health care transformation: meaningful behavior change.

Why the Hype?

It is unsurprising that AI would be the latest focus of health care hype. After all, AI, coupled with important changes in business models, underlies the disruption of industries ranging from retail to entertainment to finding transportation (eg, hailing a ride). Health care has been a laggard in these revolutions, largely because of the absence of a digital infrastructure. But that has changed. Although interoperability remains elusive and core digital tools, particularly electronic health records, are much maligned, the fact remains that health care is now collecting, storing, and moving data digitally. The so-called genetics revolution, and numerous precision medicine initiatives that are largely focused on storing and analyzing individual genetic information, have added to the massive amounts of data now available for analysis. In addition, there is interest in accessing the massive amounts of data from social media sites to help in the diagnosis and treatment of various disorders.

The business world and investor communities have noticed. Ten years ago, with much fanfare, Google and Microsoft both confidently ventured into health care only to experience sobering failure, which involved terminating (in the case of Google Health) and markedly scaling back (in the case of Microsoft HealthVault) their ambitious digital patient record initiatives. After these pain-

ful lessons, most digital giants did not get involved in health care. But that is no longer the situation. In the past few years, every major digital company has announced an AI-based health care initiative, with big dollar investments and the hiring of marquee talent.

Simultaneously, massive amounts of venture capital (\$8.1 billion in 2018) are pouring into health care digital start-ups on the premise that health care is ripe for disruption, that AI is the tool to do it, and that the winning companies will reap untold profits.⁴ It is a reasonable story, and early successes in fields ranging from insurance purchasing (Oscar, Bright) to management of chronic disease (Omada, Livongo) are fueling further investment.

The Crucial Need for an Effector Arm

The premise that more accurate and nuanced AI-based predictions will be transformative seems plausible, although that premise is likely wrong.

For example, the problem of translating evidence into practice has vexed the medical community since the evidence-based medicine movement began a generation ago. Why are only slightly more than half of evidence-based practices provided to patients?⁵ Why does it take many years between the emergence of evidence that supports a new practice and consistent implementation of that practice?⁶ Is it lack of accurate predictions? Ambiguity about the best course to take? No, neither of these are major factors.

To draw an analogy from immunology, the problem is ensuring that the effector arm functions efficiently and effectively. The body needs to identify foreign substances and organisms. But the crucial step is the activation of the immune system's effector arm—the antibody- and cell-mediated mechanisms, the complex array of cells, cytokines, complement, and more—that attack, neutralize, kill, and eliminate the intruders. Data, analytics, AI, and machine learning are about identification. But they have little role in establishing the structures, culture, and incentives necessary to change the behaviors of clinicians and patients.

For 30 years, physicians and others have tried various strategies to convert evidence about best practices into behavioral changes. For clinicians, the focus has been on education, practice guidelines, care paths, transparency, and incentives, mostly to little effect. Once the electronic health record era emerged, these strategies became digital and took the form of alerts, alarms, and order sets. However, new problems, such as alert fatigue and clinician frustration, have made clear how simplistic solutions are unlikely to be successful, even when delivered by expensive technologies rather than Post-it notes.

As for patients, consider the problem of low drug adherence. Only about 70% of all prescriptions are filled,

and of those that are filled only about 70% are taken properly for the full course of treatment.⁷ Thus, half of individuals in the United States are nonadherent with medications, and the adherence rate is even lower for patients with chronic conditions with polypharmacy. Analyzing pharmacy data and other data sources to identify nonadherent patients or, better yet, using AI to predict which patients are likely to be nonadherent and relaying that information to their care team seems logical, but it is unlikely to reduce nonadherence substantially. Medicine needs to change how physicians and other clinicians interact with nonadherent patients and change patients' medication-taking habits. Simple tech approaches, like electronic pill caps, are unlikely to fix patient nonadherence.⁸

The gurus of data seem to assume that once something is identified and known, it is solved. That might be true in the tech world, where the aim is to hound consumers with electronic ads until they click on a link and buy a product. But in the health care system the goal is often changing an ingrained habit such as eating processed foods, smoking, not exercising, or skipping daily medications. There are no data to suggest that changing the precision of a prediction—such as, for example, explaining to a patient that “there’s a very good chance your smoking will cause cancer or heart disease,” compared with “there’s a 27.6% chance your smoking will cause cancer or heart disease”—will succeed in changing behavior. The issue is the same when considering giving physicians more accurate predictions about the risk of readmission or sepsis. As Google indicated when it announced the closing of Google Health: “There has been adoption [of Google Health] among certain groups of users like tech-savvy patients.... But we haven’t found a way to translate that limited usage into widespread adoption in *the daily health routines* of millions of people” (emphasis added).⁹

The Challenge of Behavior Change

Human beings are creatures of mental and physical habits. Changing those habits requires engagement and intentionality, and thus energy, sustained over months. This is why 80% of New Year’s resolutions do not last past February.

There is a science to behavior change, and it is complex. It requires identifying triggers and changing the routine around them. It means not buying the packaged waffles but instead buying the yogurt and fruit. It could mean a patient taking medications and “rewarding” herself with morning coffee. All of this gets even more difficult when individuals are under stress.

In addition to changing patients’ routines, physician and nurse routines also need to change, along with the routines and processes of care inside health care organizations. For example, consider how difficult it has been to change the simple routine of ensuring that clinicians thoroughly wash or sanitize their hands before examining patients.

A fundamental challenge facing the US health care system is to figure out how to effectively change routines and ensure these changes are embedded in the culture of the system. AI can have a role here, but it will not be simply through better predictions. Instead, the focus needs to be on the “effector arm of AI,” thoughtfully combining the data with behavioral economics and other approaches to support positive behavioral changes. The change process will be iterative and messy, and there will be pushback. It will take place in hospitals and physician offices, not in Silicon Valley, although it is likely to require partnerships between tech companies and health care delivery organizations. Designing and implementing effector arms that induce meaningful behavior change will be the key to AI moving from the hype stage to one in which it is contributing to meaningful improvements in health and health care.

ARTICLE INFORMATION

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Health Plans, District of Columbia Hospital Association, and Washington University; holding stock in Gilead, Allergan, Amgen, Baxter, and United Health Group; and that he is a venture partner at Oak HC/FT. Dr Wachter reported serving on scientific advisory boards for PatientSafe Solutions, Early Sense, Amino, and Forward; being an investor in Smart Patients; serving on the board of directors for Accuity Medical Management; receiving personal fees from Commure, Teledoc, The Doctors Company, Nuance, GE Healthcare, Health Catalyst, AvaCare, and from approximately 50 nonprofit associations and healthcare organizations; and holding a patent to CareWeb with royalties paid.

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