Artificial Intelligence and Family Medicine: Better Together

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According to futurists, the artificial intelligence (AI) revolution in health care is here.[1] While trending now, the concept is not new and was first introduced 70 years ago when Alan Turing described "thinking machines."[2] John McCarthy later coined the term "AI" to denote the idea of getting a computer to do things which, when done by people, are said to involve intelligence.[3] What is new is the digitization of everything from electronic health records (EHRs) to genes and microbiomes, which provide the data that AI needs to learn. This conversion of images, handwritten notes, and pathology slides into 1's and 0's allows machines to perform a wide range of tasks, such as detecting retinopathy, skin cancer, and lung nodules.[4-6] Even though this surge of available data exceeds what individuals and teams can realistically manage, computers have learned how to process these data to predict outcomes important to our patients, including opioid misuse, emergency department visits, and deaths.[7-9] Advances like these led Andy Conrad, the CEO of Google's life sciences subsidiary, to declare that in medicine, "the most important tool is the computer."[10]

This revolution has proceeded without AI publications in our journals, and our discipline is missing an opportunity to shape its future. A PubMed search reveals no AI or machine learning papers in *Family Medicine*, *Annals of Family Medicine*, or the *Journal of the American Board of Family Medicine*. For comparison, AI and machine learning papers number 18, 77, and 8 for *Academic Medicine*, *JAMA*, and the *Journal of General Internal Medicine*, respectively. While family medicine scholars are engaged in AI research[11-13] and others reference it,[14] family medicine's voice needs to be amplified. Without our input, AI risks following the path of EHRs. When the Health Information Technology for Economic and Clinical Health (HITECH) Act was passed, policy makers believed that EHRs would lead to care that was more efficient, effective, and equitable,[15] and EHRs have led to important advances in population health and quality.[16] However, with increasing burnout and decreasing time with patients, many lament that EHRs cater to the needs of administrators and EHR vendors rather than physicians and patients.[17] The usability and interoperability failures underlying these complaints are not the result of gaps in technological expertise. Instead, these failures emerged, in part, because end-users like ourselves have been insufficiently engaged in relevant design, policy, and implementation decisions.

As AI spreads, our participation is needed to shape this revolution. Without our patient-centered orientation, AI has focused on delivering value to shareholders of technology companies rather than on problems that affect patients in our practices. Without our focus on value, AI has escalated health care costs and is available only to those with resources rather than those who would benefit the most. Without our focus on personal relationships, AI has further eroded face time by increasing the amount of time we spend interacting with computers. Without the breadth of our patients, AI has magnified existing biases. For example, as indicated in the literature, algorithms used by

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face recognition are less able to recognize dark-skinned pedestrians because there are too few of these individuals in training sets.[18]

While we are unsure how technology such as AI will change our jobs, we know our jobs will change, much like EHRs have changed our work over the past decade. Compared to humans, computers can process information more systematically, make decisions more consistently, and respond to changes more quickly. In health care, computers are automating repetitive and algorithmic tasks. For example, clinical decision support systems tell us when our patients are due for immunizations, at increased risk for a heart attack, or about to experience an allergic reaction to a drug we prescribed. AI can already execute complicated multistep tasks historically performed by physicians, such as generating differential diagnoses and recommending treatment plans based on the best available evidence. With computer-generated "family physicians" autonomously managing patients, it's only a matter of time before administrators start questioning the value of human ones.

Although AI has grown without publications in family medicine journals, our engagement opens new horizons by making AI more effective, equitable, and pervasive. Primary care is the largest delivery platform in the United States, providing a seminal repository of data and users.[19] We are implementation experts and we can test strategies for the adoption of evidence-based AI tools. We focus on measures that matter most to patients and will disseminate AI innovations that improve patient-centric outcomes and discard ones that do not.[20] As generalists, we collate and interpret data across not only organs but delivery systems (eg, mental health, home health, and public health). This breadth could strengthen the performance of AI tools.

While AI needs us in order to evolve, we likewise need AI. The digital future is not a passing trend. We will not return to paper charts. The volume of information we are expected to manage will not decline. Without a strategy for our digital present and future, our specialty risks being paralyzed by data, overwhelmed by measures, and more burned out than we already are. We can define our future, by embracing AI and using it to preserve our most precious resource—time with patients. Adaptation to this new reality is key for our continued evolution, and AI has the potential to make us better family physicians.[21] Using natural language processing (which helps computers understand, interpret, and manipulate human language) along with machine learning and deep learning, AI can extract information from previous encounters, imaging, labs, and health information exchanges, and assemble them into the proper places in the note so that we can focus on human interactions.[22] AI chatbots (computer programs that simulate human conversation) can facilitate patients getting the right care at the right time at the right place using the right technology, by monitoring patients in between visits and providing recommendations.[23] For example, patients with congestive heart failure can transmit their weight via internet-connected scales, and when appropriate, AI can titrate diuretic doses and ensure that patients with worsening symptoms are scheduled to see their family physicians. In addition to chronic disease management, AI chatbots can remind patients that they are due for preventive services such as breast and colon cancer screening, provide the education needed to make a decision, generate referrals, and schedule appointments to have the tests performed.[24] AI can integrate multiple data sources including geographic, EHR, claims, and pharmacy data to identify those individuals at high risk for asthma exacerbations, heart attacks, and opioid overdoses, and facilitate timely referral and appropriate treatment. With AI analyzing the avalanche of data, reporting measures, and, when appropriate, closing quality gaps, we can be more present with our patients.

While intriguing, these tools are not ready for implementation. They require substantial development, testing, and validation. There are important implications for privacy, malpractice, and overtreatment that need to be considered and addressed. In isolation, AI will have limited ability to change the delivery of care without appropriate payment models. For AI to elevate the practice of family medicine, family medicine needs to participate in relevant design, policy, payment, research, and delivery decisions.

What We Can Do

AI and family medicine can have a synergistic relationship, but getting there will require work. First, we recommend partnering with AI scholars. Find computer scientists at your institutions or in your communities. Learn about their questions, and try to shape them into ones relevant to primary care. Second, share your resources when appropriate. Your data could be used to develop new AI tools, and your clinics could serve as the laboratories that test whether these tools improve health. Finally, ask what your institutions and organizations are doing to integrate family medicine and AI. We need calls for AI papers in our journals and AI plenary speakers at our conferences. We need more AI initiatives—such as the North American Primary Care Research Group's Big Data Task Force. At the curricular level, we need to incorporate informatics into medical school curricula, residency education, residency milestones, and continuing medical education so that the next generation of family physicians is conversant in AI. At the department level, we need seed funding to stimulate collaboration between family medicine and computer scientist scholars.

As family physicians, we know that computers are not the most important tool in medicine—personal relationships are and always will be. When it comes to executing complicated tasks, computers will outperform us, but our ability to establish and sustain these relationships, understand and manage their complexity, and use them to elicit and integrate preferences into medical decisions cannot be effectively replicated. In family medicine, humans and computers are not alternatives but rather, complements, with opposite strengths and weaknesses.[25] Computers can facilitate human interactions and make the time we have with patients more meaningful. But first, we need to recognize that computers are our partners and not our adversaries.

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