

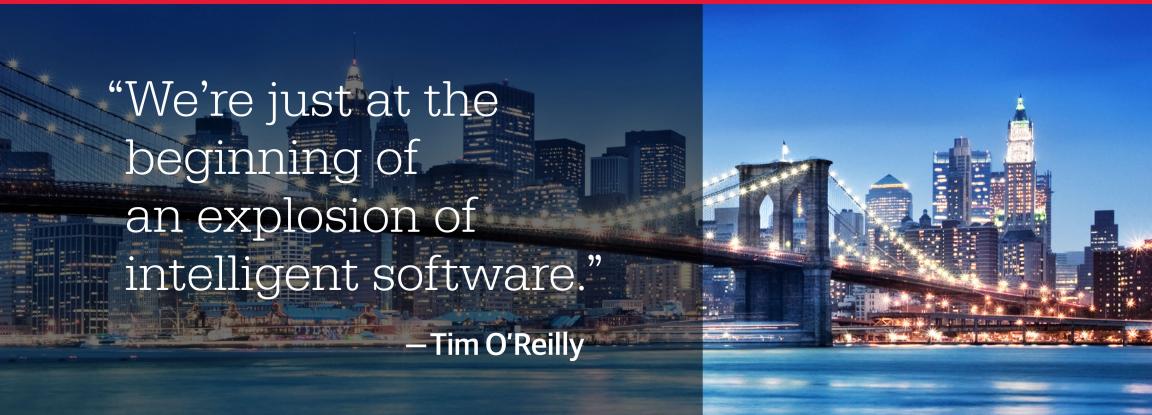
AI and Medicine

Data-Driven Strategies for Improving Healthcare and Saving Lives



Mike Barlow

Artificial Intelligence



“We’re just at the beginning of an explosion of intelligent software.”

—Tim O'Reilly

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and Saving Lives*

Mike Barlow

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by Mike Barlow

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Printed in the United States of America.

Published by O'Reilly Media, Inc., 1005 Gravenstein Highway North, Sebastopol, CA 95472.

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Editor: Nicole Tache

Interior Designer: David Futato

Production Editor: Colleen Cole

Cover Designer: Karen Montgomery

Copyeditor: Rachel Monaghan

July 2016: First Edition

Revision History for the First Edition

2016-07-08: First Release

2016-08-25: Second Release

See <http://oreilly.com/catalog/errata.csp?isbn=9781491961452> for release details.

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AI and Medicine: Data-Driven Strategies for Improving Healthcare and Saving Lives

For centuries, physicians and healers focused primarily on treating acute problems such as broken bones, wounds, and infections. “If you had an infectious disease, you went to the doctor, the doctor treated you, and then you went home,” says Balaji Krishnapuram, director and distinguished engineer at IBM Watson Health.

Today, the majority of healthcare revolves around treating chronic conditions such as heart disease, diabetes, and asthma. Treating chronic ailments often requires multiple visits to healthcare providers, over extended periods of time. In modern societies, “the old ways of delivering care will not work,” says Krishnapuram. “We need to enable patients to take care of themselves to a far greater degree than before, and we need to move more treatment from the doctor’s office or hospital to an outpatient setting or to the patient’s home.”

Unlike traditional healthcare, which tends to be labor-intensive, emerging models of healthcare are knowledge-driven and data-intensive. Many of the newer healthcare delivery models will depend on a new generation of user-friendly, real-time big data analytics and artificial intelligence/machine learning (AI/ML) tools.

Krishnapuram sees five related areas in which the application of AI/ML tools and techniques will spur a beneficial revolution in healthcare:

Population management

Identifying risks, determining who is at risk, and identifying interventions that will reduce risk.

Care management

Designing care plans for individual patients and closing gaps in care.

Patient self-management

Supporting and enabling customized self-care treatment plans for individual patients, monitoring patient health in real time, adjusting doses of medication, and providing incentives for behavioral changes leading to improved health.

System design

Optimizing healthcare processes (everything from medical treatment itself to the various ways insurers reimburse providers) through rigorous data analysis to improve outcomes and quality of care while reducing costs.

Decision support

Helping doctors and patients choose proper dosage levels of medication based on most recent tests or monitoring, assisting radiologists in identifying tumors and other diseases, analyzing medical literature, and showing which surgical options are likely to yield the best outcomes.

Applying AI/ML strategies in each of those five areas will be essential for creating large-scale practical systems for providing personalized and patient-centric healthcare at reasonable costs. In this report, I explore these areas and more through interviews conducted with leading experts in the field of AI and medicine.

A Wealth of Benefits for Millions of Patients

The potential benefits of applying AI/ML to medicine and healthcare are enormous. In addition to improving treatment and diagnosis of various cancers, AI/ML can be used in a wide range of important healthcare scenarios, including fetal monitoring, early detection of sepsis, identifying risky combinations of drugs, and predicting hospital readmissions.

“Medicine and biology are very complicated and require humans to be trained for a long time to be highly functional,” says Dr. Russ Altman, director of Stanford University’s biomedical informatics training program. “It is intriguing that computers may be able to reach levels of sophistication where they rival humans in the ability to recognize new knowledge and use it for discovery.”

ML and neural networks are especially useful, says Altman, for finding patterns in large sets of biological data. Some of the most promising applications of ML in medical research are in the areas of “omics data” (e.g., genomics, transcriptomics, proteomics, metabolomics); electronic medical records; and real-time personal healthcare monitoring via devices such as wearables and smartphones.

Real-time or near-real-time testing and analysis are particularly critical in self-management scenarios. For example, it’s essential for people with diabetes to monitor their blood sugar levels accurately. But waiting for a doctor or nurse to perform tests can impair the accuracy of results and defeat attempts to manage the disease properly. “Let’s say a test shows your blood sugar is high,” says Krishnapuram. “Maybe it was high because you ate too many carbs before the test, or didn’t sleep well the night before, or you were stressed out or didn’t get enough exercise that week. Each of those can impact your blood sugar level.”

If your doctor relies on tests performed once every couple of months at his or her office to set the proper dosage of your medication, it may be difficult to optimize your dosage and manage your condition effectively over time.

AI and ML tools can play a valuable role not only in analyzing test results rapidly and optimizing dosages of medications, but also in prompting behavioral changes by communicating timely reminders to exercise, eat healthier foods, and get more sleep.

“People also need to change their behaviors,” says Krishnapuram. AI and ML can motivate and reinforce behavioral changes by “orchestrating” multiple channels of communication between healthcare providers and patients.

Strength in Numbers

The organized practice of medicine can be traced back to 3,000 BC. Although early physicians relied on supernatural phenomena to explain the origin of many diseases, the idea of developing practical therapies for common ailments is not new. Even when the causes of disease were grossly misunderstood, physicians were expected to find remedies or provide effective treatments for patients who were sick or injured.

Today, medicine is widely regarded as a science. New therapies are invented. If they seem promising, they are scientifically tested. The tests are carefully analyzed with rigorous statistical processes. If a therapy is shown to be safe and effective in a large enough number of cases, it is approved and used to treat patients.

But in reality, that’s where the science often grinds to a halt. The overwhelming majority of healthcare practitioners aren’t scientists. The term *medical arts* isn’t merely romantic—it’s an accurate description of how medicine is practiced in most of the world.

The application of AI, ML, and other statistical processes to medical practice—as opposed to just medical research—would be a leap forward on the scale of the Industrial Revolution.

If the revolution fails, however, “we’ll look back at this century with the same sense of horror we feel when we look at previous centuries,” says Nate Sauder, chief scientist at [Enlitic](#), a company that develops ML technology for medicine. “Our feeling is that medicine—and in particular, medical diagnostics—is very much a data analysis problem,” Sauder says. “Patients generate lots of data, everything from genomic sequences to images from CT scans. It’s a natural fit for machine learning techniques.”

For example, Sauder and his colleagues at Enlitic are helping medical radiologists improve the accuracy of their diagnoses. “We chose radiology because most of the reports and images are already in digital form, which makes it easier to manage the data. There’s also

been an explosion in the improvement of computer vision technology.”

The combination of accessible data, high-quality computer vision, and ML techniques has the potential for improving the quality of care for millions of patients worldwide. “We started with a couple of the harder problems in radiology to validate our approach,” says Sauder. “For example, early discovery of lung nodules in a chest x-ray is incredibly important because there’s a huge difference in the survival rate between Stage 1 and Stage 4 cancer. We were able to identify lung nodules 40–50 percent more accurately than a radiologist.”

One reason AI/ML processes can outperform humans is that humans get tired after staring at screens for long periods of time. Another reason is that even in ideal conditions, it’s often difficult for humans to spot small cancers on a lung scan. “What makes this really challenging is that your lungs have a bunch of tiny veins running through them. In a cross-sectional slice, a small mound of cancer and a tiny vein look very similar,” Sauder says.

It’s “easier” to see the difference between tumors and veins in three-dimensional scans, but human radiologists often find it difficult to read 3D images. Software, on the other hand, can be trained to read 3D images as easily as 2D images. “As a result, a computer can look at a three-dimensional scan and can spot tumors more accurately than a human,” says Sauder. “Additionally, a machine learning system can look at 50,000 cases in the time it takes for a human to look at one case. Those advantages can be translated into saving lives.”

Workflow integration, however, is a key ingredient in determining the success of an AI/ML product or service. “We really need to appreciate that many radiologists will view machine learning as a replacement for them or as a challenge to their established workflow,” says Sauder.

Like many of the experts interviewed for this report, Sauder sees AI and ML tools and techniques as aids, not replacements, for health-care providers. He predicts AI and ML will become accepted components of the medical diagnostic toolkit when their benefits are more widely understood throughout the medical community. “Machine learning can improve diagnostics in two fundamental ways. First, it can help doctors perform diagnoses more quickly and more accurately. Second, and perhaps more important in the long

term, is applying machine learning to screening. Screening is expensive and churns out many false positives. But with machine learning, the computer can look at several hundred million screens and find the smaller, weirder things that we humans tend to miss,” he says.

The long-range promise of machine learning is its ability to sort through very large numbers of screens and discover subtle or hidden patterns linking diseases with hundreds of variables, including behavior, geography, age, gender, nutrition, and genomics. “Those hundreds of millions of screens create very rich data sets that can be culled by machine learning systems for medical insight,” says Sauder.

Barriers to Entry

Despite the promise and potential of AI and ML to revolutionize medicine, the majority of healthcare providers stick with traditional processes to diagnose and treat patients. Part of the problem is semantics. For many people, “artificial intelligence” still evokes images of sentient computers taking over the world, and very few people understand the basic concept of “machine learning.”

As a result, discussions about applying AI/ML techniques in healthcare scenarios tend to be one-sided and uncomfortable. On the other hand, most people agree that healthcare is expensive, inconvenient, and often ineffective. There is a genuine hunger for affordable solutions to modern healthcare problems, but it’s difficult for most people to understand how AI and ML can help.

Another roadblock to more widespread usage of AI and ML in medicine is extensive government regulation, which often puts a damper on innovation and creativity. “You can’t just drop new software into a medical monitor device,” says Josh Patterson, director of field engineering at [Skymind](#), an open source, enterprise deep-learning provider. “There are many regulations that create barriers to entry, making it difficult for smaller companies to compete.”

Long integration cycles also slow the adoption of new approaches based on AI, ML, deep learning, and neural networks. “Hospitals are notoriously hard to sell into unless you are an already established vendor, and established vendors are less inclined to aggressively offer new features once they have the contract,” says Patterson. “If the established vendor *does* want to offer a new ML or AI feature, then they have to figure out how to integrate it into their product.”

There are four broad obstacles to wider adoption of AI/ML techniques in healthcare, according to Krishnapuram:

- **Confusion around data ownership and privacy.** AI/ML processes are fueled by data. But which set of stakeholders owns medical data? Is the data owned by patients, doctors, hospitals, research centers, or technology vendors? Can medical data be mined for clinical insights without compromising privacy or violating existing regulations?
- **Dysfunctional incentives.** In its current form, the healthcare payment system revolves around volume of care. Shifting to a system that rewards quality of care and improved outcomes will require a fundamental overhaul of most healthcare models.
- **Liability and responsibility.** It's not clear which parties would be held accountable when something goes wrong with an AI or ML system. Who bears the risk? Who is responsible and who pays for damages? Can an AI system be sued for malpractice?
- **The traditional research paradigm doesn't support personalized medicine.** How do you conduct statistically meaningful clinical trials when each patient is treated individually and every care plan is customized for an individual patient? How do you establish baselines, set standards, and develop common procedures when each patient is a “market of one”?

“Those aren’t trivial questions,” says Krishnapuram. Resolving them will require study, public debate, legal reform, and the emergence of a new social consensus around the value of data analytics.

Amplifying Intelligence with Patient Data

Given the obstacles, it’s easy to see why healthcare organizations have been slow to adopt big data and AI/ML solutions. That said, it is imperative for society to find practical ways for solving widespread healthcare issues. AI/ML techniques offer the best and fastest path to achieving the goals of personalized, outcome-based medicine.

“Compared to other domains, such as retail and finance, healthcare is the least developed field in terms of AI and ML,” says Eric Xing, a professor in the School of Computer Science at Carnegie Mellon University. Xing has two PhD degrees, one in molecular biology

from Rutgers University and another in computer science from UC Berkeley.

Lack of medical data isn't a problem, he says. "There's a lot of data... from patients, from doctors, and from scientific studies. But the data is underused. It just sits in databases."

For example, healthcare providers collect clinical data from patients every day. But most of that information is seldom used. "It is first-hand information, collected directly from patients. It's incredibly valuable, but it's rarely looked at again unless the same patient comes back for a visit," says Xing. "So we're not making effective use of the data."

Xing's team at Carnegie Mellon is developing an AI program to integrate patient data from multiple sources such as x-rays, blood tests, tissue samples, demographics, and freehand notes from caregivers. "Once we have highly integrated data from patients, we can deploy it in a machine learning algorithm and generate predictive models," he says.

For instance, the data can be used in analytics that would help a doctor assess the risks of subdiseases associated with a patient's primary ailment or help the doctor predict the symptoms a patient is likely to experience before a follow-up examination.

AI programs can also help doctors devise safe, effective, and practical treatment plans for individual patients. "It's usually very difficult for a doctor to come up with a treatment plan unless the doctor has lots of experience treating similar patients," says Xing. "With an AI system, you can look at all the potential dangers and get a better idea of what can go wrong. The system's knowledge base includes millions of patients, and an algorithm would allow the doctor to search for similar patients in a matter of seconds."

In a very real sense, AI and ML systems enable individual doctors to expand their medical knowledge and experience far beyond what would be possible under traditional circumstances. "You can connect one patient with a database of patients, making it easier to gain deeper insights into disease mechanisms," says Xing. From the patient's perspective, "it's like assembling a large team of doctors with vast experience."

Like Sauder, Xing does not envision AI as a replacement for doctors and other healthcare providers. “The goal of an AI system is not replacing the doctor in a clinical setting. The doctor is still center stage, making decisions and delivering care.”

Xing used the analogy of autopilot systems designed for airplanes. “They aren’t a substitute for human pilots. The humans in the cockpit still make the important decisions when they see a problem. The autopilot just helps them by making it easier to fly the plane,” he says.

Pursuing the Quest for Personalized Medicine

The idea of personalized precision medicine has been around for more than two decades, but AI and ML have the potential for bringing it closer to reality. “Personalized medicine is built on the unique genetic characteristics of a patient,” Xing explains. “But it’s very difficult to practice because we don’t really understand the entire mechanisms and genetic underpinnings of many diseases. Also, the data is hard to understand. You have a million polymorphic sites, and you don’t know which one of them is actually causing the disease or just along for the ride.”

Typically, doctors check a handful of key mutations that are generally believed to be associated with a particular patient’s disease—but taking that shortcut effectively circumvents the value of personalized medicine. “When you look at a mutation that is common to many patients with a specific disease, you lose the power of personalization because everyone will be treated the same way,” Xing says.

Xing and his colleagues are building machine learning programs that analyze an individual patient’s genomic, proteomic, and metabolic data—including incremental risk factors—to generate a highly personalized profile for the patient. “You can use machine learning models for deriving the unique patterns underlying specific diseases and symptoms, as well as for identifying potential targets for drugs,” he says.

Wearables and Other Helpful Gadgets

AI will also be integral to the development of genuinely useful wearable and mobile devices for improving health. In addition to monitoring vital signs such as pulse, blood pressure, and respiration, the next generation of mobile health tech would also provide personalized real-time alerts and recommendations for modifying behavior to achieve specific health goals.

“The mobile health domain will increasingly become part of everyday life,” says Xing, who is working with his team on a mobile app to help patients with Parkinson’s disease. “It’s not just a passive timer reminding you when to take your medications. It will actually monitor your past, present, and future activity. It will monitor your environment and your risk levels. Then it will provide active suggestions for dosage, timing, and frequency of medication, and offer precautions and advice for lowering your risk.”

Xing says mobile platforms are the best way to provide patients with real-time feedback and advice. “But generating those services requires AI, because the platform must learn from the patient’s data and from existing medical data. It must be able to detect patterns in behavior and then make helpful recommendations based on those patterns,” he says.

Predicting Adverse Drug Interactions

Bartenders will tell you, “Never mix, never worry.” But many patients take more than one medication, and not everyone reacts the same way to various combinations of drugs.

“Humans aren’t very good at predicting when two drugs will interact and cause problems,” says Nicholas Tatonetti, an assistant professor of biomedical informatics at Columbia University and a member of the [Data Science Institute](#). Two drugs that are harmless when used separately might cause adverse reactions when used together by the same patient. Predicting “drug/drug interactions,” however, is notoriously difficult.

In one of their recent projects, Tatonetti and his lab colleagues looked for pairs of drugs that might cause cardiac arrhythmia. “We gathered 20 years of medical record data from Columbia and

trained a machine learning algorithm to look for drug interactions with a high probability of causing a heart arrhythmia,” Tatonetti explains. “The algorithm initially came up with about 1,000 drug/drug interaction hypotheses. Then we investigated those interactions and evaluated them for causality. We narrowed the field down to about 20 interactions—using data analysis only. There was no human intuition involved at all.”

Eventually, the machine learning algorithm identified a combination of two drugs, ceftriaxone and lansoprazole, which can generate the conditions leading to heart arrhythmia. “That is a hypothesis that nobody would have ever explored before, since those two drugs are not suspected of causing this problem,” says Tatonetti. “Because the algorithm we trained to look for arrhythmia found a pattern, it was able to identify this new and potentially dangerous drug interaction.”

Machine Learning Is Key to Better, Faster Medical Research

Human beings are great at seeing “the big picture.” We assemble a universe around ourselves by sampling bits and scraps of information, and then creating stories and narratives on the fly. We’re always taking mental shortcuts—the “fast thinking” heuristics described so well by Daniel Kahneman and Amos Tversky.

But when it comes to understanding and managing complex phenomena—like cancer and Alzheimer’s disease—our innate human ability to rapidly leap from a handful of facts to a sweeping conclusion is our Achilles heel.

Machine learning is a potential antidote to our highly evolved, but not always useful, talent for manufacturing reality from information gathered by our senses. Machine learning excels at identifying latent patterns and connections that we are too highly evolved to perceive. We create myths by ignoring or skipping over details. Machine learning, on the other hand, happily feeds on minutia.

Most diseases, it turns out, are made up of smaller subdiseases, which themselves are caused by even smaller subdiseases. Multiple layers of interrelated biological processes are involved, making it highly difficult to apply simplistic “rule of thumb” approaches.

Machine learning's ability to find patterns and to uncover hidden relationships among subdiseases is what makes it especially attractive to medical researchers. For example, one of the harder problems in medical research is bridging the gap between genetics and disease phenotypes. Here's a quick and useful definition of the genotype/phenotype distinction from the *Stanford Encyclopedia of Philosophy*:

The genotype is the descriptor of the *genome* which is the set of physical DNA molecules inherited from the organism's parents. The phenotype is the descriptor of the *phenome*, the manifest physical properties of the organism, its physiology, morphology, and behavior.

Despite an abundance of genomic and phenotype data, bridging the gap between the genome and disease phenotypes requires a shift to computational models that incorporate the causal complexity inherent in our biology, says David Beyer, a principal at [Amplify Partners](#) and author of *The Future of Machine Intelligence: Perspectives from Leading Practitioners*.

"In the last decade, researchers have transitioned from the application of shallower machine learning techniques (primarily linear in nature) to a new class of approaches, including *deep learning*, a subclass of ML broadly defined around the idea of multilayered neural networks," says Beyer. "And just as deep learning has shown breakthrough performance in categories such as vision, the hope is to extend that success to biology and medicine."

Insight from Yeast

The genotype-phenotype divide has limited the practical value of genomic science in treating disease, since people with the same genetic mutations can experience different symptoms of the same disease, or in some instances, experience no symptoms at all.

Genomic medicine is also an area in which machine learning techniques can generate highly valuable insights. At Tatonetti's lab, researchers studied yeast genetics to understand why some human gene mutations are harmless by themselves, but deadly when combined with other mutations. The phenomenon is called *synthetic lethality*, and it's a hurdle that makes it difficult to use genetic information for curing human diseases.

Understanding synthetic lethality in humans is critical to developing targeted and personalized cancer therapies that spare healthy cells

while killing cancer cells. “We know a lot about synthetic lethality in yeast, but it’s hard translating that knowledge from yeast to humans,” Tatonetti explains. “Humans have 5 to 10 times more proteins than yeast. So the number of potential interactions is exponentially higher in humans than in yeast.”

Many of the previous attempts to use yeast for understanding more about human disease had been unsuccessful because they focused on the mechanism of the proteins themselves. “We took a different approach,” says Tatonetti. “We set up a supervised machine learning algorithm and told it which pairs of genes were synthetic lethal to yeast. Then we applied the algorithm we had trained on the yeast to making predictions for human genes. The algorithm didn’t know it was looking at human genes; it just ran. And it predicted about a million lethal pairs of human genes.”

The team then compared the algorithm’s output to a previous highly detailed investigation of lethality in human cancer cells. “We validated our findings against the smaller ‘gold standard’ set and found that we had achieved practically the same performance.”

Tatonetti and his colleagues successfully deployed a machine learning algorithm for translating knowledge from unicellular organisms to multicellular organisms. “Instead of trying to understand the functions of every protein in the human body, we let the machine identify the important patterns for us,” he says.

AI Is “Like a Small Child”

If there’s a rock star of AI in medicine, it’s Dr. Lynda Chin, associate vice chancellor and chief innovation officer at the University of Texas System. “The human brains are limited in their capacity,” she says. “Medicine is becoming more and more complex, as more and more data are collected about the patients and the medical knowledge base grows exponentially. No single human being can possibly keep up, especially if their job is taking care of patients. We need help.”

Chin sees AI as a helpful tool for augmenting human cognitive capabilities. AI would serve doctors in much the same way that paralegals or law clerks serve trial lawyers and judges. Paralegals and clerks aren’t substitutes for lawyers and judges, yet they are necessary for an effective legal system. For example, AI can help doctors

organize and synthesize the ever-increasing amount of data—about the patients, the disease, and the treatment options—into intelligence that is actionable.

“Imagine if a doctor can get all the information she needs about a patient in 2 minutes and then spend the next 13 minutes of a 15-minute office visit talking with the patient, instead of spending 13 minutes looking for information and 2 minutes talking with the patient,” says Chin.

However, she describes AI in medicine as maturing, still a small child who is growing up fast. “Training AI systems to be useful in medicine is like parenting—no easy task! Not only does the underlying AI analytics need to mature, application of AI in medicine itself is a brand new challenge that requires an iterative learning process.”

It’s All About Sharing the Data

From Chin’s perspective, one of the biggest barriers to developing and applying AI in medicine is access to longitudinal medical and other health-related data that truly represent the diversity of the patient population and the heterogeneity of the diseases. “These data are all over the place, not shared, and worse yet, not standardized, with each silo being too small and too narrow...which means they’re not good for training an AI system,” she says.

Learning from her earlier work in partnership with IBM Watson to develop MD Anderson Oncology Expert Advisor®, a virtual cognitive expert system designed to democratize cancer care knowledge and expertise, Chin believes that the promise of AI in medicine will remain elusive until the barrier to data is removed. “The sharing needs to go beyond individual hospitals or hospital systems,” she says, “because no single entity has enough data.”

In her effort to remedy the data challenge, Chin began working with PricewaterhouseCoopers to develop a “super-compliant” cloud platform for sharing medical data and analytic insights safely and securely across disparate institutions and organizations.

A necessary component of the platform is a governance framework to assure all stakeholders that the data will be used only for the specific purpose, with no unspecified secondary uses. “Rarely anyone objects to the stated use of data,” she says. “It’s the unintended or unexpected use of private data that worries most people. We need to

acknowledge the importance of keeping data private, even when it is shared.”

To achieve that goal, her group is also partnering with AT&T to develop secure dedicated networks for transmitting healthcare data. “We need security and privacy when data is transmitted, not just when it’s at rest,” she says.

In addition to a cloud-based infrastructure that can securely connect to disparate data sources across health and other related industries, she hopes to see “more data from more patients and more institutions, more networking and more aggregating of data from more sources.”

Chin also envisions application of these novel technologies and capabilities in the battle against access and affordability of healthcare for the disadvantaged in medical desert areas. “We need to think about providing care for the people who can’t afford or don’t have access to healthcare,” she says. “AI, along with wearables and mobile devices, can potentially extend more affordable and quality care to these people.”

Looking Ahead

As a sexagenarian Baby Boomer, I now interact with the healthcare system more often than ever before. From my perspective as someone who writes frequently about data science, I am regularly astonished and dismayed at how poorly my medical information is collected, stored, analyzed, and shared. No retailer would ever countenance the indifference to data that is routinely demonstrated by healthcare workers at practically every level.

As a child, I was taught that medicine is both a science and an art. I have seen the art part in action. Watching skilled medical practitioners set broken bones or slice away diseased tissue is like watching miracles being performed.

Like many people, I’m still waiting for the scientific part of medicine to really kick into high gear. Clearly, AI and its various components have the potential to play enormous roles in improving many aspects of healthcare. But the full potential of AI in medicine won’t be realized until there’s a new social consensus on healthcare data.

It's time to begin a national dialogue about how we treat healthcare data. Will we treat it as private property that is owned and sold, or will we treat it as common property that is shared freely? The answer to that question will largely determine the eventual impact of AI on medicine.

About the Author

Mike Barlow is an award-winning journalist, author, and communications strategy consultant. Since launching his own firm, Cumulus Partners, he has worked with various organizations in numerous industries.

Barlow is the author of *Learning to Love Data Science* (O'Reilly, 2015). He is the coauthor of *The Executive's Guide to Enterprise Social Media Strategy* (Wiley, 2011), and *Partnering with the CIO: The Future of IT Sales Seen Through the Eyes of Key Decision Makers* (Wiley, 2007). He is also the writer of many articles, reports, and white papers on numerous topics such as smart cities, ambient computing, IT infrastructure, predictive maintenance, data analytics, and data visualization.

Over the course of a long career, Barlow was a reporter and editor at several respected suburban daily newspapers, including the *Journal News* and the *Stamford Advocate*. His feature stories and columns appeared regularly in the *Los Angeles Times*, *Chicago Tribune*, *Miami Herald*, *Newsday*, and other major US dailies. He has also written extensively for O'Reilly Media.

A graduate of Hamilton College, he is a licensed private pilot, avid reader, and enthusiastic ice hockey fan.