

Mark L. Braunstein

Practitioner's Guide to Health Informatics

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As a teacher I try to never forget the impact that we can have—sometimes in just a single conversation—on a young person's life.

Dr. David M. Kipnis died a few months before I began writing this book. He was chairman of the Department of Internal Medicine at Washington University. Toward the end of my incredibly demanding internship he unexpectedly summoned me to his office. To say the least, I was quite nervous. We had little interaction that busy, often hectic year during which I was subsumed by the care of very sick patients, often basically on my own and in a major hospital setting.

He immediately asked something like: "Do you know why you were accepted to this program?" I had no answer (and feared I was about to hear something awful about my performance). He went on to explain that he, personally, had selected me because of my highly unusual combination of interests in medicine and computing, something he said would be very important over the coming years.

That comment particularly struck me because I never had an interest in medicine until, several years earlier, Dr. Leroy S. Lavine, a prominent physician and my cousin by marriage and whom I greatly respected, asked me what I planned to do after graduating from MIT. It was the sixties, a crazy time, and I told him I had no idea. He advised me that my strong interest in computing should be directed toward medicine because it would be an important and growing field over the course of my career. Even having never previously considered medicine, I followed his advice.

Kipnis then went on to say that I was not a traditional candidate for a prestigious program like Washington University—I'm sure it was clear from my medical school record that I had spent far more time programming than learning to be a doctor—and that his concern about accepting me had been whether I could actually be a good doctor. I imagine I was pale white by then, so he let me off the hook by saying I had actually done very well, and urged me to continue, even suggesting I could earn a faculty appointment in his department to pursue medical informatics, once I was done with my training.

Similar to the conversation with Dr. Hiram Curry which I'll relate in the Introduction, I told him I was honored by his interest in me, but I wanted to take a year off to see if I could finish the work on the pharmacy system I had developed at MUSC. His response was something

I'll also never forget. It was something like this: "I'd like to see you stay in medicine but no one achieves a great deal in life unless they pursue their real passion."

One year became two, and I never went back. In truth, health informatics was my passion and I owe it to Drs. Kipnis, Lavine, and Curry for helping me figure that out. As a result, I am honored to be able to dedicate this book to them.

PS: In my current role at Georgia Tech, I'm often approached by students (sometimes medical students from nearby Emory) with similar conflicts about their future direction and I invariably tell them the Kipnis story and give them the same advice he gave me so many years ago.

Why I Wrote This Book

As a medical student at the Medical University of South Carolina (MUSC) in the early 1970s I fell under the spell of the late Prof. Hiram B. Curry, a former general practitioner who said that job was so hard that he went to Harvard to study neurology! Years later, he founded MUSC's cutting edge academic department of family medicine. I needed a summer job and he was looking for students to help find families for his new clinic, so I arranged a Friday afternoon interview. After he described the job, I gathered the courage to say that I wanted to do something else—computers in medicine. Instead of laughing, he gave me a copy of Dr. Larry Weed's then-new book, *Medical Records, Medical Education and Patient Care*. I read it—twice—over the weekend. Returning to his office Monday morning, I said excitedly that Weed was right and computerized problem-oriented medical records were the future. Over the next few years we developed one of the first fully operational ambulatory electronic medical record (EMR) systems.^{1,2} Today it might even be described as an electronic health record (EHR) because it encompassed virtually all of a patient's care. With the advice and counsel of Dr. William Golod, Dean of the MUSC School of Pharmacy, and John D. James, RPh whom he brought in from industry to run our dedicated, on-site pharmacy, we developed a particularly rich subsystem with advanced clinical functionality for the time, including interaction screening and monitoring patient compliance based on refill intervals.³ We had numerous visitors and the pharmacy component of our system attracted a great deal of interest. With the school's help, two colleagues and I started a company to create a commercial, standalone version of the pharmacy system. Both Kaiser (starting with their Southern California region under the guidance of Al Carver, someone to whom I owe a great debt for taking a chance on a very young, very green entrepreneur) and the U.S. Military Health System

¹Office of Technology Assessment 1977. Policy Implications of Medical Information Systems. <http://ota-cdn.fas.org/reports/7708.pdf>.

²Braunstein, ML, Schuman, SH and Curry, HB 1977. "An On-Line Clinical Information System in Family Practice," J Fam Pract, 5:617–26.

³Braunstein, ML and James, JD 1976. A Computer-Based System for Screening Outpatient Drug Utilization, J of Am Pharm Assoc, NS16:82–85.

(Tri-Service Medical Information System or TRIMIS) installed it successfully, and our tiny company attracted the interest of a much larger, public company that eventually acquired it. As a result, I left MUSC and ended up spending the next three decades or so in the commercial health information technology (HIT) sector.

Since 2007, when my last company was acquired, I've been teaching health informatics at Georgia Tech. In 2012, I published *Health Informatics in the Cloud*, a short guide to the field written with nontechnical readers in mind. Based on it, I developed what may have been the first Massive Open Online Course (MOOC) in the field and, to my amazement, a third of the 20,000 students who enrolled in its two sessions were either physicians, nurses, or other healthcare providers. Many more were in other positions in the healthcare delivery industry. Over this same period of time the U.S. has achieved widespread adoption of electronic records and patient-facing healthcare tools, but these technologies often still have limitations. Many providers are unsatisfied with them and don't feel there are benefits that warrant the pain of learning to use them well. A key reason for this is that they don't talk to each other, so the focus has now largely shifted from adoption (which is where it was when I wrote the earlier book), to interoperability, how to make these systems talk to each other and how to use the digital "big data" derived from them to improve health care through analytics. The clear interoperability "crisis" has spawned, with astonishing speed for health care, the development and even acceptance of "radical" new and far better technical approaches to data sharing.

This convergence of events convinced me there was a need to update the earlier book substantially while maintaining it as a practical guide to the field. What started as a rewrite morphed into a very different book, written more specifically for busy healthcare providers but still suitable for all nontechnical readers. I hope it makes the potential of health informatics in patient care far clearer and more exciting to providers. For all readers, I hope it will provide a sense of where we are on what has been a long journey that still has much further to go. Most importantly, I hope it will excite you to learn how health informatics—if properly conceived, implemented, and used—can help move us to a more effective, efficient, and safer healthcare system.

For the most part, this book is not technical. I've highlighted the sections that do go into technical detail so readers with no interest in that can skip ahead. Doing so should not impede your ability to grasp the key concepts I hope to convey. At the same time, for those of you who want more technical detail, I have provided many links and references to related information that is almost all freely available on the Internet.

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Mark L. Braunstein

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Of course, any remaining problems are my responsibility alone.

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