Healthcare: A Better Way

The New Era of Opportunity
Sir Isaac Newton is known to have said, “If I have seen further it is by standing on the shoulders of giants.” This certainly captures the circumstances of this book. The intent of the book is to provide the reader a concise overview of the challenges facing healthcare, the emerging solutions to those challenges and a glimpse of an exciting new future for our noble profession. As such, the book represents very little original thought on my part. Rather, it is a compilation of the works of many visionary leaders that I have had the good fortune of encountering throughout my professional career. I am deeply indebted to each of these great leaders for sharing their wisdom, insights and experience.

My good friend Brent James, MD, is a deeply inspirational leader who has patiently and steadfastly worked for three decades to improve healthcare and inspire healthcare leaders both nationally and internationally. He has had an immense impact on me and on countless others. David Burton, MD, recognized the importance of quality improvement early in his career, and through his visionary leadership as both a clinician and an operational leader he demonstrated that quality improvement could be successfully integrated into the complex process of care delivery. I do not know any two clinicians who have demonstrated this more effectively in a real-world care delivery environment than David and Brent. Robert Wachter, MD, has had a greater impact on increasing awareness of the issues related to patient safety and done more to advance the cause of patient safety than any physician leader I know. Bob’s book on patient safety, “Understanding Patient Safety” (Second Edition), is the quintessential resource on this important topic. Along with Dr. James, my dear friend, Molly Coye, MD, co-authored the seminal Institute of Medicine (IOM) reports To Err Is Human and Crossing the Quality Chasm. Molly has contributed greatly to advancing awareness of quality in healthcare and to our understanding of the role of emerging technologies in the future of care delivery. Steve Barlow, Tom Burton and Dale Sanders are phenomenally creative leaders in information technology (IT) and healthcare analytics, and they have incredibly deep experience in architecting and deploying successful technology and analytics solutions. Holly Rimmash, RN, has two decades of experience in improving clinical care, including implementation of clinical and operational best practices. Cherbon VanEtten is knowledgeable in IT, analytics, clinical operations and education. She was a valuable member of the editing team. Dan Burton, the CEO of Health Catalyst®, is an imaginative, kind, intelligent and supportive leader who has skillfully guided Health Catalyst to ever-increasing success. Dan also had the wisdom and courage to support this project. Paul Horstmeier has launched and grown three different businesses and won numerous industry awards for quality and innovation. It is healthcare’s good fortune that Dan and Paul are now applying their deep experience to transforming healthcare. Leslie Falk, RN, provided her clinical expertise, and experience in engineering, business and
marketing. Leslie has been a joy to work with on this project. Sister Monica Heeran, CSJP, is one of the most supportive and thoughtful leaders I have ever known. Without her vision and willingness to take a risk with a young physician leader, my career would never have been the same. John Hayward has been a longtime mentor and friend. He has more passion for improving healthcare than any non-clinician that I have ever known. I am indebted to Elaine Dunda and Donn McMillan. Working alongside Elaine and Donn, I was able to gain deep, pragmatic experience in successfully implementing quality and safety into a complex integrated care delivery environment. Last, but certainly far from least, I would like to recognize the thousands of clinical and operational leaders across the country who are daring greatly and working tirelessly to improve care for patients and communities. They are an inspiration to all of us.

These are the shoulders on which I stand and on which this book is built.

John L. Haughom, MD
INTRODUCTION

Daring greatly

To have lived through a revolution, to have seen a new birth of science, a new dispensation of health, reorganized medical schools, remodeled hospitals, a new outlook for humanity, is an opportunity not given to every generation.

Sir William Osler (1849–1919)

The great Sir William Osler wrote these words in April 1913, near the end of his career and six years before he died. He lived and practiced during a time of great change in healthcare. Over the roughly three decades between 1880 and 1915, Sir William and a few dozen other visionary clinicians laid the foundation for modern clinical care. The physical layout and operational structure of the modern hospital was initially defined. The basic four-year medical school curriculum (two years of basic science and two years of on the ward clinical experience) was established. Postgraduate educational requirements were articulated. Strict licensure requirements for physicians were put into place. The first textbooks of medicine and surgery were written. Scientific research was made the foundation for clinical practice. Foundations for modern nursing practices were created. New hygiene practices to prevent infection were implemented.

Over the past century, we have clearly enhanced and improved these practices and added new advances. Yet, it remains true that we owe a great debt to these visionary clinicians. We are still living their legacy. There was a need for change. These visionary leaders rose to the challenge and charted a new course for healthcare that has lasted more than a century and remains the basis for the way care is provided around the world.

Our turn to create a new vision

This is a difficult and challenging time in healthcare. Once again, we are facing a profound need for change. Anyone involved in leadership and the practice of care knows this is the case. We face an unprecedented level of complexity that is overwhelming our systems and the people trying to practice within them. Far too many outcomes are inadequate. While “first do no harm” is our mantra, we know that the level of harm patients experience when seeking our services is not acceptable. According to the Institute of Medicine (IOM), an estimated 44,000 to 98,000 deaths per year result from avoidable harm. Costs are out of control and waste is widespread. Far too many people lack access to basic health services. The list goes on.
The healthcare world is changing, and for good reason. Now it is our turn to create a new vision and chart a new course for clinical care and for health. Certainly, anyone involved in healthcare leadership, and arguably everyone involved in healthcare, should participate. Clinicians have a professional responsibility to be involved. This is the foundation of why we exist. Physicians, nurses and other care providers need to change the system. We need to create a system of care delivery that allows those working in it — in collaboration with patients — to achieve its potential on behalf of the patients and communities we serve. While many will be involved in this transformative endeavor, it will not be any different than 100 years ago. Pioneering clinical leaders can — and must — lead the way. They have the knowledge of clinical care and the focus on patients that is necessary to successfully lead change. We need to stand on the shoulders of giants to glimpse — and create — a new and better future for healthcare. Working to improve patient care is a noble cause of the first order.

One can make an effective argument that we have adequate resources. However, those resources are definitely not being efficiently used to meet the care requirements of those in need in our society. Organizations need to improve access to and the consistency, quality, safety and cost of care, in addition to eliminating unnecessary waste. Accomplishing this requires a deep understanding of clinical and operational processes in addition to an ability to design, adopt, implement and manage new, more efficient care delivery processes and care delivery models. While this will require a true multidisciplinary, highly collaborative approach, real success will mandate the passionate engagement of clinical leaders and front-line clinicians. Without capturing the hearts and minds of clinicians, it will be very difficult for any organization to successfully negotiate the tumultuous changes over the next few years. Thus, while this educational resource is designed to inform and engage many stakeholders, it is particularly aimed at informing and engaging physicians, nurses and other healthcare providers.

Knowledge source for those who dare greatly

This book represents the compilation of the works of many. It is designed to be a knowledge source for clinical and operational leaders, as well as front-line caregivers, who are involved in improving processes, reducing harm, designing and implementing new care delivery models, and generally undertaking the difficult task of leading meaningful change on behalf of the patients we serve. It is designed to be a living document. This generation’s healthcare leaders need to frame the need for change in language and with logic that appeals to the values of stakeholders. They also need to articulate
a compelling new vision for care, explain how that vision will be achieved, and help individual stakeholders understand their role in achieving and sustaining this new vision. It is hoped this book will be a resource for leaders engaged in this critically important change endeavor. This book started out, and will remain, primarily as a digital document, which will allow frequent updates and adaptations as events rapidly unfold and progress is made.

Thanks to some pioneering individuals and organizations, we can now see enough of the future of healthcare to have a sense of what it will be. And it is exciting. Empowering. Better for patients and communities. The new ideas, vision, tools and methods capable of supporting meaningful change are falling into place. As progress is made, the digital format of this book will allow it to evolve as rapidly and often as necessary. In that sense, this book will never be done, nor should it be. Like all of healthcare, this is a knowledge tool that should be, and will be, a continuous improvement experience.

No doubt, this is a time of adversity in healthcare. As hard as it is, one can view adversity as a privilege and an opportunity. During times of great change and adversity, we cannot control circumstances, but we can change how we view them. We need to lean into the adversity. Many involved in the healthcare profession need to see a glimpse of the future, understand their role in it and be sustained by a sense of hope. It is our responsibility — and privilege — to offer this to them.

Three years before Sir William wrote the quote at the beginning of this introduction, Theodore Roosevelt delivered the following words in a speech:

'It is not the critic who counts; not the man who points out how the strong man stumbles, or where the doer of deeds could have done them better. The credit belongs to the man who is actually in the arena, whose face is marred by dust and sweat and blood; who strives valiantly; who errs, who comes short again and again, because there is no effort without error and shortcoming; but who does actually strive to do the deeds; who knows great enthusiasms, the great devotions; who spends himself in a worthy cause; who at the best knows in the end the triumph of high achievement, and who at the worst, if he fails, at least fails while daring greatly, so that his place shall never be with those cold and timid souls who neither know victory nor defeat.'

Theodore Roosevelt, 1910

This quote is certainly pertinent to the situation we currently face in healthcare. We are experiencing one of those “opportunities not often given” described by Sir William. Change is hard, and those of us involved in it feel how hard it is. If Sir William — and other early pioneers — were alive today, I am confident they would look around and say, “Ah yes … — yes. This is
where we need to be.” This is where we need to be as well. We need to stay in the arena and “dare greatly.”

So, welcome to the arena. I am glad to be here with you. I hope the information in this dynamic book helps you see and prepare for an exciting new future.

I invite you to join me in making this book the best support tool it can be.

John L. Haughom, MD
February 2014
In this chapter, we will cover the historical, cultural, financial and social forces that define and shape the U.S. healthcare system as it exists today.
What’s good about U.S. healthcare: 100 years of progress

We hear a lot lately about the problems with healthcare in the U.S. While the need to improve quality and decrease costs is real, let’s not forget to celebrate what is good about our healthcare system. It is worthwhile to briefly review the past 100 years of history to emphasize one point: our healthcare is the best the world has ever seen!

Consider these simple examples:

- From 1900 to 2010, average life expectancy at birth increased from only 49 years to almost 80 years.¹
- Since 1960, age-adjusted mortality from heart disease (the #1 cause of death) has decreased by 56 percent.²
- Since 1950, age-adjusted mortality from stroke has decreased by 70 percent.³

Why so much progress over the last 100 years? Let’s explore a few of the historical trends.

The emergence of modern medicine

For much of history, if you were ill or injured and saw a physician, your chances of survival actually went down. Hospitals were the places where people went to die. Actually, hospitals were the places where the poor went to die. If you had any resources at all, you invited a physician into your home … and you died at home.

Just prior to 1900, this all changed profoundly as a result of the vision and hard work of a handful of visionary clinical leaders (William Osler, William Halsted, Howard Kelly, Florence Nightingale, William Welch, Harvey Cushing, etc.). It is possible to credit the change to a handful of impactful advances in the medical profession:

- New, high standards of clinical education
- Strict requirements for professional licensing
- Clinical practice founded on scientific research
- New internal organization for hospitals
- Creation of new, more modern nurse practices
- Implementation of more modern hygiene techniques
- New public health policies and treatments

Since that time, we in the medical profession routinely achieve miracles.
A century of strides in public health and patient care

It is illuminating to look at the change in life expectancy in the U.S. since 1900. Figure 1 shows that a child born in 1900 had a life expectancy just shy of 50 years. For a child born 110 years later, the life expectancy is 78 years — an increase of over 28 years! This is an amazing accomplishment and, frankly, something unseen in the prior 6,000 years of recorded human history (where life expectancy remained relatively flat).1

Much of this increase can be attributed to improvements in public health. That’s why the first half of the 20th century could be called the Public Health Era. Advances in public health led to a gain of about 3.5 years in life expectancy with each passing decade. The increase was largely due to avoiding epidemics of infectious disease such as cholera, typhus and smallpox.

Then, sometime between 1950 and 1960, two things happened:

1. We largely exhausted (though not completely) public health as a major source of increase in life expectancy.

2. For the first time, we began to document gains in life expectancy in the population as a whole from treatment provided in hospitals and clinics. You’ll notice that the curve on the graph flattens out a bit at this point — a gain of about 1.3 years of life expectancy per decade. Though less than the public health increase, against the sweep of human history, the gain driven by clinical care is still phenomenal.

We stand on the foundation of 100 years of science that has massively improved our understanding of the human organism in health and disease and given us thousands of ways to improve the well-being and life expectancy of patients.

Only in the last 60 years have we been able to show that clinical care can make a difference. This is in the lifetime of many people involved in healthcare today. We can do more than just predict whether a patient will live or die. We can actually change the outcome. We are the first generation of clinicians that can make that claim. That’s something that I’m proud and excited to be a part of.
Does history matter?

All of this history is important because it changes how we think about the present and future. No doubt, we face many challenges. As healthcare increasingly contributes to the national debate, let’s debate in the context of the phenomenal progress we’ve made and the progress we’re capable of making. And let’s remember that at least 95 percent of our peer clinicians get up every day seeking to be the best they can be for the patients they serve. They have a deep-seated professional expertise and a passion for quality that can be tapped as we seek to address the challenges and transform the system.

The primary determinants of health: The Great Equation is wrong

It is not hard to make the case that American healthcare is the best the world has ever seen. However, it is also easy to effectively argue that there is vast room for improvement. Paradoxically, the profession is falling significantly short of its theoretical potential. This does not negate the obvious advances made over the past century, but it is important to understand this reality because it is the source of much of the current criticism.

The healthcare Great Equation

In 1977, Aaron Wildavsky, an American political scientist known for his work on public policy, published a book entitled “Doing Better and Feeling Worse: The Political Pathology of Health Policy.” In the book, Wildavsky argued that the traditional belief that “medical care equals health,” the so called “Great Equation,” simply wasn’t true. Most of the bad things that happen to people are at present beyond the reach of medicine. More available medical care does not equal better health.

Determinants of how well we live

One of the most-cited statistics in public health is the imbalance of social investments in medical care compared with prevention activities. Approximately 95 percent of the trillions of dollars we spend as a nation on health goes to direct medical care services, while just 5 percent is allocated to population-wide approaches to health improvement. However, some 40 percent of deaths are caused by behavior patterns that could be modified by preventive interventions, as shown in Figure 2. Genetics, social circumstances and environmental exposure also contribute substantially to preventable illness. It appears, in fact, that a much smaller proportion of preventable mortality in the U.S., perhaps 10 to 15 percent, could be avoided by better availability or quality of medical care. Thus, one could question a funding scheme that places so much emphasis on medical care rather than prevention.
The fact that medical care historically has had limited impact on the health of populations has been known for many years. The data clearly indicates we could achieve a much greater impact on total health by going after behaviors than by delivering care.

To put this in perspective, a study published in the British Medical Journal tracked approximately 35,000 people over about 20 years. The study looked at 4 behaviors related to health (tobacco use, appropriate alcohol use, diet and exercise) and demonstrated that people who did well on all 4 compared to people who did poorly on all four accounted for a 14-year difference in life expectancy. Compare this to all of healthcare delivery accounting for approximately 3.5 to 7 years of additional life expectancy.

**How this impacts the healthcare policy debate**

Doctors have little or no control over 90 percent of factors that determine health, from individual lifestyle (smoking, exercise, worry), to social conditions (income, eating habits, physiological inheritance), to physical environment (air and water quality). Most of the bad things that happen to people are at present beyond the reach of medicine.

Everyone knows that doctors do help patients. We can mend broken bones, cure most infections and successfully operate on diseased organs. Inoculations, infections and organ repairs are good reasons for having doctors, drugs and hospitals available. More of the same, however, is likely counterproductive. Nobody needs unnecessary operations, and excessive use of drugs can create dependencies or adverse reactions resulting in patient harm.

More money for clinical care alone cannot advance health. In the absence of medical knowledge gained through new research, or of administrative and clinical knowledge to advance common practice into best practice, current medicine has gone as far as it can. It will not produce more if more money is applied, and one could argue that we should be advancing anyway, especially...
with the extensive expenditures that the U.S. already applies to clinical care and the well-defined levels of wasted resources that could be applied to advancing clinical care.

Spending on health is not necessarily bad. Would we rather spend our disposable income on a new car, a more powerful personal computer or a TV instead? The problem is that healthcare spending as a percent of disposable income in the U.S. is growing much faster than disposable income itself is growing (see discussion of healthcare spending below). This growth in healthcare spending is impacting other categories of spending — such as education and other socially beneficial programs. The argument is not that clinical care is bad, only that it is not good for everything. The marginal value of spending an additional dollar — or 1 billion dollars — on medical care is likely to be close to zero in terms of improving health.

A simple look at healthcare inflation demonstrates why this has caused policymakers to increasingly take a hard look at healthcare costs in the U.S. In 1960, per capita health costs in the U.S. were $146. In 2012, the per capita costs exceeded $8,000. While there has been a return on this societal investment, it has not been as great as one would want. In addition, as healthcare costs move beyond 20 percent of gross domestic product (GDP), it is becoming an increasing burden for both the public and private sector. The U.S. spends far more on health as a percent of GDP than other industrialized countries. This is making it hard for the U.S. to compete in an increasingly globalized economy.

The twofold solution

The solution to this national dilemma is twofold:

1. First, we need to slow the rate of growth in spending on healthcare.

2. Second, we have to spend what we devote to healthcare more efficiently. That is, we need to realize greater value from the resources dedicated to clinical care.

Published studies indicate the rate of waste in healthcare is somewhere between 30 to 50 percent. The causes of waste need to be eliminated. This is where aggressive, data driven process improvement enters the picture. Experience at leading healthcare delivery organizations has clearly shown that clinician-driven performance improvement can improve outcomes, reduce harm, increase patient satisfaction, reduce waste and save large sums of money. Such value-based performance improvement efforts can assure that waste is eliminated and health expenditures are more efficiently used.

In addition, new, more efficient, patient-centric, and ambulatory based care delivery models need to be implemented. The National Committee for Quality Assurance (NCQA) Medical Home is a clear example of this trend.
Technology and advanced data management will play a role in enabling these new care models. Several studies have shown that these technology-enabled models of care can reduce the annual costs to manage some high-profile chronic diseases by up to 40 percent. Given that roughly two dozen chronic diseases account for almost 75 percent of U.S. health expenditures, these new models of care offer great potential to address healthcare inflation. They have also been shown to allow clinicians to manage more patients, which will help address a growing clinician shortage, especially of physicians and nurses.

The old equation is wrong. It is time for a new equation. In a world of increasingly constrained resources, individual life cannot be the sole determinate of how we allocate resources.

The Rule of Rescue

In 1986, U.S. bioethicist Albert Jonsen described the so-called “Rule of Rescue.” In Jonsen’s words:

Our moral response to the imminence of death demands that we rescue the doomed. We throw a rope to the drowning, rush into burning buildings to snatch the entrapped, dispatch teams to search for the snowbound. This rescue morality spills over into medical care, where ropes are artificial hearts, our rush is the mobile critical care unit, our teams the transplant services. The imperative to rescue is, undoubtedly, of great moral significance; […]

John McKie and Jeff Richardson subsequently defined the Rule of Rescue as “the imperative to rescue identifiable individuals facing avoidable death, without giving much thought to the opportunity cost for doing so.”

Note their use of the key phrase “identifiable individuals.” The Rule of Rescue describes the moral impulse to save identifiable lives in immediate danger at any expense. Think of the extremes taken to rescue a small child who has fallen down a well, a woman pinned beneath the rubble of an earthquake, or a submarine crew trapped on the ocean floor. In these situations, no effort is deemed too great.

The Rule of Rescue has held particular significance in the U.S. where the importance of the individual has long been a part of our cultural fabric. In the U.S., we tend to count ourselves as not fully human unless we pull out all the stops. Increasingly, however, healthcare ethicists and policymakers are asking whether this same moral instinct to rescue, regardless of cost, should be applied in the emergency room, the hospital or the community clinic.
Rule of Rescue examples

Statistics and costs tend not to invoke as much passion among the American public as individual cases of clinical need. For example, it has been estimated that 29,000 children around the world, mostly in poor countries, die every day from readily preventable causes, yet there is no outpouring of media attention, public or private donations or aircraft carriers steaming out to rescue them. We will readily spend hundreds of thousands of dollars on organ transplants and other procedures that may give a few months of limited life to someone, while we don’t spend much smaller sums that could prevent many cases of premature illness and death. The estimated cost for prophylactic Factor VIII to treat one patient with hemophilia for one year is $300,000. Costs of this magnitude have been accepted by public and private insurers in the developed world, even though, in principle, these sums could provide greater overall health benefit if allocated to pay for the unmet healthcare needs of many other patients.

Let’s look at various forms of “rescue care” by nation, comparing the U.S. to major European countries (France, Germany and the United Kingdom), based on Organization for Economic Cooperation and Development data (OECD, 2009). First, the prevalence of renal dialysis (Figure 3) and kidney transplants for chronic renal failure (Figure 4).

The prevalence of renal dialysis and renal transplant in major European countries is substantially less than in the U.S. It is not that these countries do not have patients that would benefit from dialysis and transplant.
It is a matter of public policy in using renal dialysis and transplant in the treatment of advanced renal failure. The U.S. uses these interventions extensively — European countries much less so.

Now, let’s look at the mortality rate from acute myocardial infarction (AMI) in Figure 5, comparing the U.S. with major European countries.

Once again, it is not that the European countries do not have ischemic heart disease. Rather, the point is that AMI is treated much more aggressively with all potential treatment modalities in the U.S. compared to major European countries.

Finally, let’s compare mortality rates from cancer between the U.S. and major European countries, as shown in Figure 6.

Cancer is equally prevalent in Europe as it is in the U.S., but we tend to treat it much more aggressively here, offering patients every opportunity to be cured, or at least to extend their lives.

Despite spending twice as much as the average Western European country on its healthcare (see discussion on health expenditures below), the U.S. lags behind on a number of health system performance indicators, including amenable mortality — that is, deaths that could have been avoided with timely and effective healthcare. Examples of such conditions include diabetes and acute infections, as summarized in Figure 7.12
The impact on total health

In terms of “total health” as measured by mortality amenable to timely and effective medical care, the U.S. does not do as well. The reason for this discrepancy is the U.S. does not focus on primary care and prevention. We place a heavy focus on rescue care. Many countries outperform the U.S. as a result of better public health, a greater focus on behaviors and better primary care. However, the U.S. performs significantly better for those with severe illness or injury (i.e., in terms of rescue care) as a result of better access to technology, less explicit rationing and easy access to subspecialists.

Going forward, as pressure to control healthcare costs grows and the need to manage precious resources more carefully increases, the broad application of the Rule of Rescue will be increasingly untenable. But the cultural and moral instinct to apply it will continue. The desire to help those weakest among us will remain strong, especially when their small numbers allow us to see them as unique individuals. This will likely be a very difficult cultural norm for American society to manage as healthcare transformation unfolds.

The impact of patient expectations and healthcare consumerism

Whenever one is ill or injured, there is an understandable high expectation the best care will be available and everything that can be done will be done. While this is likely a universal human desire, or even an expectation, it is particularly true in the American tradition and culture. In addition, as exemplified during the capitation experiment during the 1990s, patients also have high expectations when it comes to choice. They also understandably have high expectations for a caring provider. Survey data and experience suggest patients value their relationship with a trusted clinical advisor more than any other element in healthcare delivery.
It is unlikely these expectations will change in the future. However, as healthcare costs increase and patients are increasingly expected to share a greater portion of the cost burden, when and how these expectations are met is likely to evolve.

As patients become “customers,” they are increasingly likely to take charge, and become more attuned to and knowledgeable regarding issues ranging from outcomes and safety rates to increasing insurance deductibles and co-pays. They will pay attention to the costs of diagnostic studies and treatments, and to the nuances of regulatory changes and healthcare reform. Financial insecurity, high unemployment, evaporating assets and savings, and increasing healthcare cost burdens will only add momentum to these trends. Enhanced knowledge will almost certainly result in profound changes to the way patients view and interact with healthcare providers.

Understanding these shifts in patient expectations and how their behaviors are likely to change will be an important step in coming years. Healthcare providers need to be aware of these changes and know how to measure and address them. Recognizing and adapting to these changes will impact everything from patient satisfaction to clinical outcomes, patient flow, models of care that are more patient centric and ambulatory centric, reimbursement, and legal liability risks, making healthcare providers more competitive and less vulnerable.

Meeting patient expectations is more than accommodation — it is risk management because happy patients do not sue. It keeps providers competitive and results in improved clinical care. Good patient experiences lead to better outlooks, improved outcomes, and an enhanced sense of security and wellbeing.

The role of variation in clinical practice

Jack Wennberg, MD, and other health service researchers have documented extensive variation in the delivery of healthcare in many parts of the world. Information on practice variation is important for examining the relationships between policy decisions and clinical decisions. Variation differences also raises important questions concerning the efficiency and effectiveness of healthcare. Variations in healthcare delivery and utilization can indicate potential opportunities to reduce costs and improve the value of healthcare delivery without compromising patient care.

Variations in healthcare spending across the U.S. have been well documented by Dr. Wennberg as well as other federal and state agencies. The National Health Expenditure data show total per capita healthcare spending ranging from $4,000 in Utah to $6,700 in Massachusetts. Spending variations across smaller geographic units have also been documented using Medicare data. County-by-county analyses by the National Center for Policy Analysis show
Medicare per capita spending in 2008 varied from just over $5,000 in Nobles County, Minnesota, to $8,500 in Rice County, Kansas. Similarly, researchers with the Dartmouth Atlas Project found that among 306 hospital referral regions, Medicare spending per patient ranged from more than $16,000 in some areas to less than $6,000 in others.

Policymakers want to know why healthcare spending is higher in some areas than in others. More specifically, they want to know if there are some efficiencies in low-spending areas that could be replicated in higher-spending areas, thus reducing healthcare costs overall.

In evaluating practice variation, clinical care can be grouped into three categories with different implications for patients, clinicians and policymakers:

- **Effective care** is defined as interventions for which the benefits far outweigh the risks. In this case the right rate of treatment is 100 percent of patients defined by evidence-based guidelines to be in need, and unwarranted variation is generally a matter of underuse.

- **Preference-sensitive care** is when more than one generally accepted treatment option is available, such as elective surgery. Here, the right rate should depend on informed patient choice, but treatment rates can vary extensively because of differences in professional opinion.

- **Supply-sensitive care** comprises clinical activities such as doctor visits, diagnostic tests and hospital admissions, for which the frequency of use relates to the capacity of the local healthcare system. Among older Americans, most of these services are used in caring for chronic illness. However, regions with high rates of use of supply-sensitive care do not have better overall outcomes as measured by mortality and indicators of the quality of care, suggesting the problem in the U.S. is overuse of this category of care.

Due to unique patient and/or care-setting characteristics, there will always be a degree of appropriate variation in the practice of medicine, even for patients with the same diagnoses. It is clear, however, that through the use of evidence-based and data-based approaches to clinical decision-making, hospitals and other providers across the country can do much more to reduce inappropriate or unwarranted variation.

Inappropriate variation in clinical practice occurs when non-evidence-based care is provided, or when lacking widely accepted evidence-based care, the high level of variation cannot be supported on a quality or outcomes basis. Such care is often driven by nonclinical factors, such as legal, financial, operational (hospital or other care unit processes), or other considerations that providers bring — consciously or unconsciously — to the process of making decisions about how patients are treated. Inappropriate variation can lead to reputational problems for healthcare providers, whether physicians,
other clinical staff or affiliated organizations, and often leads to disparate outcomes for patients — either unanticipated or suboptimal outcomes — and higher utilization, costs and waste. The more healthcare providers base their care on good evidence and good data, and the more they standardize their care on best practice, the more they are likely to avoid these pitfalls.

The topic of variation will be discussed in considerably more detail in future chapters.

**U.S. healthcare spending**

Healthcare spending is the biggest financial issue facing the nation. Spending on healthcare in the U.S. has been growing precipitously for over three decades and neared $2.6 trillion in 2010, over 10 times the $256 billion spent in 1980, as portrayed in Figure 8.\(^{16}\)

The rate of growth in recent years has slowed relative to the rate of growth in the late 1990s and early 2000s but is still expected to grow faster than national income over the foreseeable future, as summarized in Figure 9. Addressing this growing burden continues to be a major policy priority at both the national and state level.\(^{16}\)

In the private sector, employer-based coverage has been a mainstay benefit for decades. Since 2002, premiums for employer-sponsored health coverage for a family have increased by 97 percent, placing increasing cost burdens on employers and workers. An increasing number of U.S. businesses are less
competitive globally because of ballooning healthcare costs. Furthermore, the U.S. has been in a recession or experienced tepid growth for much of the past decade, resulting in higher unemployment and lower incomes for many Americans. U.S. economic woes have heightened the burden of healthcare costs for both individuals and businesses. These conditions have focused even more attention on healthcare spending and affordability.

As a result of these trends, employers are steadily reducing health insurance coverage or eliminating it altogether. An example of this is IBM’s recently announced plans to move about 110,000 retirees off its company-sponsored health plan and instead give them a single fixed payment to buy coverage on a health-insurance exchange. This is a clear sign that even big, well-capitalized employers aren’t likely to keep providing the once common benefits as medical costs continue to rise. The move, which will affect all IBM retirees once they become eligible for Medicare, will relieve the technology company of the responsibility of managing retirement health-care benefits. In announcing the decision, IBM said the growing cost of care makes its current plan unsustainable without big premium increases. IBM’s shift is an indication that health-insurance marketplaces, similar to the public exchanges proposed under the Affordable Care Act, will play a bigger role as companies move coverage down the path taken by many pensions, paying employees and retirees a fixed sum to manage their own care. In the future, increasing premiums and growing marketplace competitiveness will likely lead more employers to reduce or drop coverage.

Many consumers and small employers are also struggling to afford their health insurance premiums. Some employers are not able to offer healthcare coverage at all. For firms with fewer than 10 employees, only 50 percent offered coverage to their workers in 2012. As a result:

- 49 million Americans lacked health insurance in 2011.\(^\text{17}\)
- Those consumers with healthcare coverage experienced a 7.2 percent increase in their share of healthcare costs between 2011 and 2012. Healthcare costs for American families in 2012 exceeded $20,000 for the first time.\(^\text{18}\)
- Increasingly, Americans are having problems paying for care — 26 percent report they or a family member had problems paying medical bills in the past year. Fifty-eight percent of Americans reported foregoing or delaying medical care in the past year.\(^\text{19}\)

In the public sector, Medicare covers the elderly and people with disabilities, and Medicaid provides coverage to low-income families. Enrollment has grown in Medicare with the aging of the baby boomers and in Medicaid due to the recession. This means that total government spending has increased considerably. Escalating healthcare costs also are straining federal and state
budgets, hindering the nation’s ability to pay for important initiatives needed to address other significant issues. In total, health spending accounted for 17.9 percent of the nation’s Gross Domestic Product (GDP) in 2010, as shown in Figure 10.

The U.S. spends far more per capita in both the public and private sectors than any other nation in the world, as illustrated in Figure 11.

These and vast amounts of other spending data make it abundantly clear that change is inevitable. These healthcare spending trends are unsustainable, and in the future they will make change inevitable as private payers, public payers and consumers demand the elimination of waste, better utilization of resources in delivering high-quality and safe care, and new, more efficient care delivery models.

In later chapters of this book, a strong case will be made that high-quality, readily accessible data, sound analytics and effective improvement methodologies are essential to address the quality, safety, access and satisfaction challenges facing healthcare. This is no less true when it comes to addressing healthcare’s cost and waste challenges.

In the next chapter, we will examine the quality, safety, complexity and human factors that make up the present and future challenges facing healthcare. Following that, in part 2, we will turn our attention to emerging evidence-based and data-driven performance improvement solutions that healthcare providers can implement to address these challenges and more adequately provide patients and communities the care they deserve.
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APPENDIX A:
HEALTHCARE: A COMPLEX ADAPTIVE SYSTEM

Defining complexity science

Complexity science is the study of complex adaptive systems, the relationships within them, how they are sustained, how they self-organize and the outcomes that result. Complexity science is made up of a variety of theories and concepts. It is a multidisciplinary field involving many different areas of study, including biology, mathematics, anthropology, economics, sociology, management theory, computer science and others.

Complexity science is built on modern research and concepts that view systems as nonlinear and able to adapt to a changing environment. Complexity science considers characteristics of systems that are overlooked by conventional mechanical approaches. It offers a framework for studying complex adaptive systems, focusing on the patterns and relationships among the parts in order to understand and act on the unpredictable aspects of working with people in dynamic organizations.\textsuperscript{148,149}

A complex adaptive system is a collection of individual entities that have the ability to act in ways that are not always totally predictable. Furthermore, the entities’ actions are interconnected: one entity’s actions can sometimes change the context for the other entities and thereby impact the other entities’ actions in unpredictable ways. Examples of complex adaptive systems include the environment, the immune system, the stock market, a colony of insects, world financial markets and families.

Mechanical versus complex theories

For centuries, scientists viewed the world and events as being linear. Their world was one where simple cause-and-effect rules could generally explain events and outcomes. Everything was viewed as a machine. If you carefully took the machine apart and gained understanding of the parts, you could then understand the whole. Scientists embraced the belief that the universe and all of its components could be dissected, understood and ultimately controlled.

However, in the modern era, this view of the universe and its parts began to falter. Despite intensive study, many systems did not behave in this manner. The weather, ecosystems, economics, political systems and, increasingly, organizations as they became larger and more complex, could not be predicted by mechanical theory. Despite using the most powerful computers in the world,
these types of systems, and others like them, remained unpredictable and hard to understand. Ultimately, as science entered the world of quantum physics, the reality that mechanical theory could not explain everything became more obvious. Increasingly, new discoveries made it apparent that the very smallest nuclear subcomponents simply did not behave in accordance with simple cause-and-effect rules. They were governed by a different set of principles.

As scientists in different disciplines explored these phenomena, a new theory began to emerge that better explained the behavior and outcomes of these complex systems: complexity theory. In a complex system, the system is made up of components that can act independently and interact in a way that is unpredictable. Yet these interactions, and the system as a whole, ultimately can be explained by complexity theory.

You can distinguish between systems that are fundamentally mechanical and those that are naturally adaptive. Conventional (mechanical) models are based on Newtonian scientific principles that view the universe and its subsystems as machines. In the Newtonian approach, the theory holds that by understanding simple, universal rules that control the system’s parts, future behavior of the parts is predictable with linear cause and effect. Even complex mechanical systems rarely produce unpredictable behavior. When they appear to, experts can generally sift through the data and determine the cause. For example, when a computer system crashes, it may appear that the outcome was unpredictable. However, more often than not, you can decipher the cause after a thoughtful and thorough review of the evidence. A reasonable argument can be made that this framework for understanding how machines work guided the orientation of medicine around organ-based disciplines and physiological processes and healthcare organizations around linear, hierarchal relationships and rules.

Conversely, the agents within a complex system interact and connect with each other in random ways. Complexity science helps make regularities become apparent, it helps form a pattern that feeds back into the system, and it informs the interactions of the agents within the system and the behavior of the system as a whole. For example, if an organism within an ecosystem begins to deplete one species, the result will be a greater or smaller supply of food for others in the system, which affects their behaviors and numbers. Following a period of flux across all the different populations within the ecosystem, a new balance or steady state emerges.

**The growing interest in complexity theory**

The interest in complexity science has grown rapidly over the past decade. One of the reasons for this is the emergence of highly complex, worldwide challenges, including the environment, understanding the human genome, healthcare and medicine, economics, world markets, population growth and
telecommunications, to name a few. Another reason is the emergence of advanced computing resources with sufficient power to model large-scale, complex systems, to investigate new ways of approaching system design and to predict the outcomes for a given model. With advanced computing systems, experts are able to effectively study large-scale, complex, highly adaptive systems, like healthcare.

Organisms, people and organizations are parts of networks within complex adaptive groups. They interact, adapt and learn. For example, organisms are the adaptive agents within an ecosystem; antibodies are the adaptive agents in the immune system; humans are the adaptive agents in the political system; and organizations are the adaptive agents in the economic system. Each agent acts based on its knowledge and experience, and all agents interact together, while adapting to the environment. In complex adaptive systems, the parts have the freedom and ability to respond to stimuli in different and unpredictable ways. As a result, unpredictable, surprising and even innovative behaviors and outcomes become real possibilities.

**Complexity theory and organizations**

Although its roots are clearly in science, complexity theory is increasingly being used outside of science to help describe, understand and predict the behavior of other complex entities, including organizations. Complexity science can help you understand how an organization and its subcomponents adapt to their environments and how they cope with complexity and uncertainty. From the perspective of complexity science, organizations are not viewed as aggregations of individual static entities that behave in predictable ways. Rather, they are viewed as a dynamic collection of strategies and structures that are adaptive. That is, their collective behavior will evolve and self-organize in response to change, initiating events or collections of events that can be explained by complexity science. By understanding the tenets of complexity science, leaders of complex organizations can better understand and lead their organizations. However,

<table>
<thead>
<tr>
<th>Complex adaptive systems</th>
<th>Traditional systems</th>
</tr>
</thead>
<tbody>
<tr>
<td>Are living organisms</td>
<td>Are machines</td>
</tr>
<tr>
<td>Are unpredictable</td>
<td>Are controlling and predictable</td>
</tr>
<tr>
<td>Are adaptive, flexible, creative</td>
<td>Are rigid, self-preserving</td>
</tr>
<tr>
<td>Tap creativity</td>
<td>Control behavior</td>
</tr>
<tr>
<td>Embrace complexity</td>
<td>Find comfort in control</td>
</tr>
<tr>
<td>Evolve continuously</td>
<td>Recycle</td>
</tr>
</tbody>
</table>

Figure 105: Comparison of organizational system characteristics
this requires leaders to view and lead their organizations differently than they have traditionally.

Organizational management theorist Gareth Morgan, Ph.D., contrasted complex adaptive systems and traditional systems, as shown in Figure 105.\textsuperscript{150} Change and innovation are major characteristics of complex adaptive systems, as opposed to the simple, linear and additive relations that are characteristic of Newtonian, mechanical thinking. Behaviors and outcomes can be good or bad, advances or failures. Outcomes can occur either at the microsystem level (for example, an outcome resulting from a relationship of trust between a patient and a physician) or at the macrosystem level of care (such as the AIDS epidemic).

Complexity science views individual organizations as part of a connected web of interacting agents embedded in larger networks and systems, distinct from traditional top-down, linear, prescriptive, bureaucratic hierarchies. Living in this world of organizational interconnections can create an uncontrollable and oftentimes turbulent environment. The consequences of people interacting in a complex organizational system (especially those with slim resources) can contribute to leaders feeling like they are living in a world of unpredictable disruptions, not a world of understandable trends. As they continue to operate in this context, leaders need to become more skilled in managing contradictions and competing demands. In Figure 106, Morgan contrasts the leadership styles necessary to lead in a complex adaptive system environment as compared to a traditional system.

<table>
<thead>
<tr>
<th>Complex adaptive systems</th>
<th>Traditional systems</th>
</tr>
</thead>
<tbody>
<tr>
<td>Are open, responsive, catalytic</td>
<td>Are controlling, mechanistic</td>
</tr>
<tr>
<td>Offer alternatives</td>
<td>Repeat the past</td>
</tr>
<tr>
<td>Are collaborative, co-participating</td>
<td>Are in charge</td>
</tr>
<tr>
<td>Are connected</td>
<td>Are autonomous</td>
</tr>
<tr>
<td>Are adaptable</td>
<td>Are self-preserving</td>
</tr>
<tr>
<td>Acknowledge paradoxes</td>
<td>Resist change, bury contradictions</td>
</tr>
<tr>
<td>Are engaged, continuously emerging</td>
<td>Are disengaged, nothing ever changes</td>
</tr>
<tr>
<td>Value persons</td>
<td>Value position, structures</td>
</tr>
<tr>
<td>Shift as processes unfold</td>
<td>Hold formal position</td>
</tr>
<tr>
<td>Prune rules</td>
<td>Set rules</td>
</tr>
<tr>
<td>Help others</td>
<td>Make decisions</td>
</tr>
<tr>
<td>Are listeners</td>
<td>Are knowers</td>
</tr>
</tbody>
</table>

Figure 106: Comparison of leadership styles
Viewing healthcare as a complex adaptive system

As discussed in chapter 2, most people would agree healthcare is overwhelmingly complex. In the 1960s, the typical general practitioner practiced in a privately owned office with minimal staff, subscribed to one or two journals, periodically engaged a specialist when necessary, rounded on their patients in the hospital and did roughly an hour’s worth of paperwork a week. The specialist was completely independent, practiced primarily in the hospital, focused primarily on a particular body system, was in total control of their practice and interacted with administrators only when they needed some type of support (e.g., a new device).

Those days are essentially gone. As thousands of new drug therapies, sophisticated new forms of diagnosis and treatment, the need for computerization, demands for integrated care, rising demands for data-driven quality outcomes, increasing costs, growing legal liabilities, complex new regulations, and a host of other complex, interrelated forces entered the scene, the complexity of clinical care grew exponentially. With these changes, the practice of care has become stressful and often overwhelming for both clinicians and non-clinicians, from individual providers, nurses, general practitioners and specialists to administrators and senior executives.

As the healthcare environment becomes even more complex, it is increasingly exceeding the ability of the smartest and most well-trained clinician to consistently make the best possible decisions. Studies have shown humans can deal with approximately seven (plus or minus two) independent variables when making any given decision, regardless of how smart or how well educated they are. Yet clinicians encounter situations almost every day that require juggling far more than seven variables. For example, Alan Morris, MD, demonstrated there are about 240 factors to consider when adjusting a ventilator for a patient in an intensive care unit. Although Dr. Morris concluded that only about 40 of these were the most important, that number still vastly exceeds the ability of the unaided human mind.

Regardless of the clinical environment in which they practice, busy clinicians and health system leaders face multivariable, complex decisions every day. Given their human limitations, it is not surprising they would find it difficult to consistently make the right decision. As healthcare becomes even more complex, it will be increasingly necessary to build standardized processes, care environments and decision-support systems that allow clinicians and others to be the best they can be.

In Appendix A of the IOM’s Crossing the Quality Chasm report, Redesigning Health Care With Insights From the Science of Complex Adaptive Systems, Paul Plsek defined a system as “the coming together of parts, interconnections, and purpose.” While systems can be broken down into parts that can be individually interesting, the real power lies in the way the
parts come together and are interconnected to fulfill a given purpose. The U.S. healthcare system is made up of numerous parts (hospitals, clinics, laboratories, pharmacies, urgent care centers, imaging centers, physician groups, insurers, etc.) that are interconnected by patients and the flow of information to fulfill a specific purpose — improving and maintaining the health of patients and populations.

It is easy to demonstrate that the U.S. healthcare system and its many stakeholders (patients, care providers, operational stakeholders, payers, policymakers, society, etc.) represent a complex adaptive system. While there are certainly pockets of mechanical systems within healthcare, the individual parts and the collective whole largely represents a complex adaptive system.

In his book *The Checklist Manifesto: How to Get Things Right*, Atul Gawande points out that complexity theory divides decisions and problems into three general categories: simple, complicated and complex. Simple problems are ones in which the inputs and the outputs are known. These problems can be managed by following a set of rules. Complicated decisions involve significant uncertainty. In these situations, the solutions may not be known, but they are potentially knowable. Finally, complex decisions are decisions in which the actual formula for success is unknowable. You may have a general sense for what works, but you do not know with certainty what will work, nor do you know the outcome with any degree of certainty. Raising a child is a good example. You can raise children using the best available, experienced-based guidance, yet the outcome is definitely not predictable.

It is important to understand the differences between these three categories of decisions and problems because the approach you take needs to match the type of problem you face. For example, a surgical checklist or simple datasets have been proven to be good solutions for simple problems. However, a checklist or a simple dataset is unlikely to be of much help for a highly complex decision. The best approach to a complex decision is often to try something that seems to make sense based on your knowledge and the available data. You must then measure the results and often repeat the cycle many times in search of the best possible outcome. This data-driven approach is increasingly being used in clinical care and will be become even more common in the future.

Complexity science can guide your understanding of the healthcare system, a multilayered system driven largely by rapidly changing demands, technology and information. In healthcare, organization and practitioner components make up a continuously evolving system because of their innovative, diverse and progressive adaptations. Understanding the core processes of an organizational system is critical. Core processes are the building blocks of the organizational system.
Studying the interfaces and interactions of core processes allows health system leaders to ask questions based on flows and patterns among the processes, identify feedback loops, explore interfaces and interactions and ultimately recognize the elements of an efficient system. If the components of a complex adaptive system act collectively, broken healthcare system interconnections can be identified and changed. When interactions among these components encounter boundaries, those boundaries can constrain effective interactions and limit outcomes. For example, if the traditional silos that have characterized our healthcare system persist (e.g., physicians, hospitals, insurers, etc.), they will impede the development of efficient accountable care organizations that can effectively manage the health and wellbeing of populations.

Whether you look at population health management or individual patient care, the traditional approach to patient care delivery and health system leadership does not encompass the complexity and behavior of the whole system. In managing individual patient care, clinicians tend to pay attention to linear episodes of care, one organ or disease at a time. However, the body has multiple systems, and treatment directed to one organ system or disease potentially affects the entire body.

The same is true of health system leadership. Healthcare organizations tend to focus their resources on treating, restoring and maintaining their own system integrity. Like the human body system, the healthcare organization has multiple, interconnected components. Healthcare delivery organizations are complex organizational forms, and they operate in an environment that is among the most complex of the world’s organizational environments. Hundreds of different types of professionals and organizations interact to provide a wide variety of services to patients, their families and their communities. Fragmentation and specialization, much of it well intended, characterizes both the delivery of health services and healthcare policy. We often fail to appreciate how these separate components interconnect. Similar to multiple organ failure in illness, failure of healthcare organizations to reach their potential often results from a failure to understand relationships and interactions between subcomponents. This can lead to significant dysfunction, or worse, the failure of the system. It also prevents the realization of optimal care for patients and communities.

Going forward, complexity science will play an increasing role in the design of new care delivery systems and models (at both the microsystem and macro-system level) and in the development of new policies designed to shape and transform our healthcare delivery system. Readers interested in learning more about viewing healthcare as a complex adaptive system and the application of complexity science to healthcare can access a variety of available resources.20, 155, 156
APPENDIX B: UNDERSTANDING DATA TYPES IN HEALTHCARE

In chapter 4, we covered the concept of processes and systems, the elements of frequency distributions, how to understand the different types of variation (common cause and assignable) and how they relate to processes. We also reviewed the concept of statistical process control and how it helps differentiate common cause variation from assignable variation, how statistical process control (SPC) charts are created, how SPC charts are applied and tampering. Professionals involved in healthcare improvement should understand these concepts.

We will now turn our attention to the different type of data and the types of SPC charts associated with each data type. Some readers who are involved in improvement will find this information beyond what they need or want to know. The information is included for those who want to delve more deeply into the topic.

When applying statistical process control methods to healthcare, it is important to recognize and understand the different types of data one encounters. Data are the actual pieces of information that are collected or observed during the process of delivering care. For example, if you ask five physicians how many inpatients they are managing, they might provide you the following data: 0, 3, 1, 5 and 16 (the latter physician might be a hospitalist who covers an intensive care unit). These represent examples of discrete data. Not all data are numbers. For example, if you record the gender of each of the patients in a physician’s practice, you might get the following data: male, female, female, male and female.

Most data fall into one of two groups: categorical (or attribute) data and numerical data. The characteristics of these data types are illustrated in Figure 107.

<table>
<thead>
<tr>
<th>Categorical data</th>
<th>Numerical data</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Nominal</strong></td>
<td><strong>Discrete</strong></td>
</tr>
<tr>
<td>Values or observations can be assigned a code in the form of a number where the numbers are simply labels. You can count but not order or measure nominal data. Examples: sex, eye color, etc.</td>
<td>Values or observations can be counted (1, 2, 3…) and are distinct and separate. Examples: the number of patients on a panel, the number of doses of a medication delivered, the number of instruments counted, etc.</td>
</tr>
<tr>
<td><strong>Ordinal</strong></td>
<td><strong>Continuous</strong></td>
</tr>
<tr>
<td>Values or observations can be ranked (put in order) or have a rating scale attached. You can count and order but not measure ordinal data. Examples: low/medium/high, poor/good/excellent, Stage I/Stage II/Stage III, etc.</td>
<td>You can measure continuous data. Values or observations may take on any value within a finite or infinite interval. Examples: height, weight, time, temperature, etc.</td>
</tr>
</tbody>
</table>

Figure 107: Data types
Categorical (attribute) data

Categorical data are observed variables that can be sorted into groups or categories based on their characteristics or attributes. Another name for categorical data is qualitative data. There are two types of categorical data seen in healthcare: nominal data and ordinal data.

As the name implies, nominal data refer to named categories. Nominal data are items that are differentiated by a simple naming system based on their observed characteristics or attributes, such as a person's gender, marital status, ethnicity, birth date or a DRG category.

Nominal data often have two categories (“alive” or “dead,” “male” or “female,” “present” or “absent”). That is, it is binary. Nominal data can take on numerical values (such as “1” indicating male and “2” indicating female), but those numbers do not have mathematical meaning. For instance, you cannot add 1’s and 2’s for male and female together and have it make any sense. This type of data are most often summarized with counts, proportions or rates. For example, “a proportional of the total” is binary. Nominal data in binary form generally have a binomial frequency distribution. Proportion charts (p charts) are often used to describe attribute data. These represent the most common type of control chart in healthcare. There are also specific statistical tests that are used in analyzing nominal data (i.e., $X^2$ test, Fisher's exact test, etc.).

Ordinal data mix numerical and categorical data. The data fall into categories, but the numbers assigned to the categories have meaning. They are ordered, named categories. Observations on an ordinal scale are set into some kind of order by their position on the scale. Observations may indicate things such as temporal position, superiority, worsening, etc. For example, rating a hospital or clinic on a scale from 0 stars (lowest) to 5 stars (highest) represents ordinal data. Other examples of ordinal data include low/medium/high, Stage I/Stage II/Stage III/Stage IV, and poor/fair/good/very good/excellent. Ordinal data are often treated as categorical, where the groups are ordered when graphs and charts are made. However, ordinal data contain more information than nominal data. Unlike categorical data, the numbers do have mathematical meaning. For example, if you survey 100 people and ask them to rate a hospital on a scale from 0 to 5, taking the average of the 100 responses will have meaning. This would not be the case with nominal data. This type of data is generally summarized with counts, proportions or rates. An example of a statistical test used in analyzing ordinal data is the Jonckheere-Terpstra test. The Jonckheere-Terpstra test takes advantage of the ordered categories. Therefore, it has more power than the statistical tests used on nominal data (e.g., $X^2$ test, Fisher’s exact test). From a practical perspective, more statistical power means a test can extract more information and is better able to detect assignable variation when it does occur.
Numerical data

These data have meaning as a measurement, such as a person’s height, weight, IQ or blood pressure. Alternatively, they are a count, such as the number of patients in a physician panel, an instrument count following surgery or how many patients a physician can see in a clinic every day. Statisticians often refer to numerical data as quantitative data. Numerical data can be further broken into two types: discrete and continuous.

- Discrete data represent items that can be counted. The most common form of discrete data are the cardinal numbering system (0, 1, 2, 3,), which is commonly used in healthcare. Discrete variables are measured across a set of fixed values, such as age in years (not microseconds). A person will say, “I am 20 years old” — not, “I am 20.672 years old.” These are often arbitrary scales, such as scoring one’s level of satisfaction, although such scales can also be continuous.

- Continuous data represent measurements. These measures are tracked along a continuous scale that can be divided into fractions or described down to multiple decimal points, such as temperature. Continuous variables allow for infinitely fine subdivisions, which means that if your measurements are sufficiently accurate, you can compare two items and determine the difference.

There are two types of numerical data that are most often seen in healthcare: interval data and ratio data.

Interval data are measured along a scale in which each position is equidistant from the one before and after it. This allows for the distance between two pairs to be equivalent. Examples of interval data include a satisfaction scale rated from 1 to 10, temperature in degrees Fahrenheit and dates on a calendar. This type of data contain more information than ordinal data. Interval data are generally described using intervals on a real number line. Interval data do not have a meaningful zero. As a result, interval data cannot be multiplied or divided. The values for interval data cannot be counted, nor can they form meaningful ratios. Interval data are usually summarized using means and variances (standard deviations). An example of interval data is the Celsius or Fahrenheit temperature scale. A person’s temperature generally ranges from 95 to 105 degrees Fahrenheit. At any given time, one’s temperature can be 98.6 degrees, 99.2 degrees or any one of numerous other points along the temperature scale. Interval data are uncommon and rarely part of an improvement project in healthcare.

Ratio data are numbers that can form meaningful ratios. Examples in healthcare include weight, age, blood pressure, and cost. Ratio data can be either continuous (e.g., can take on any numeric value, such as cost or weight) or discrete (e.g., meaningful only at discrete values, such as number of children). Ratio data contain more information than interval, ordinal or nominal data. In a ratio scale, numbers can be compared as multiples of one another.
For example, a person can be twice as tall as another person. In addition, the number zero has meaning. Thus, the difference between a person of 35 and a person of 38 is the same as the difference between people who are 15 and 18. A person can also have an age of zero. Ratio data can be multiplied or divided because the difference between 1 and 2 is the same as the difference between 3 and 4, and, 4 is twice as much as 2. This type of data are summarized with means and variances (standard deviations). Statistical tests that use ratio data include ANOVA and regression analysis.

**Parametric and nonparametric distributions**

There are a variety of different SPC charts. The choice of which SPC chart you use depends on the underlying frequency distribution of the data type being analyzed. There are two general types of frequency distributions: parametric and nonparametric.

A parametric distribution is shown in Figure 108. Parametric frequency distributions have an equation that describes the shape of the frequency distribution. The equation has parameters (variables). Most useful distributions have a single parameter that is the mean, or average. A few distributions have two parameters (mean and variance). Some rare distributions add a third parameter (mean, variance and offset from origin).

The characteristics of parametric and nonparametric distributions are shown in Figure 109.

<table>
<thead>
<tr>
<th>Parametric and nonparametric distribution characteristics</th>
<th>Parametric</th>
<th>Nonparametric</th>
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<tbody>
<tr>
<td>Assumed distribution</td>
<td>Normal</td>
<td>Any</td>
</tr>
<tr>
<td>Assumed variance</td>
<td>Homogenous</td>
<td>Any</td>
</tr>
<tr>
<td>Typical data type</td>
<td>Ratio or interval</td>
<td>Nominal or ordinal</td>
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<tr>
<td>Data set relations</td>
<td>Independent</td>
<td>Any</td>
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<tr>
<td>Usual central measure</td>
<td>Mean</td>
<td>Median</td>
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<tr>
<td>Benefits</td>
<td>Can draw more conclusions</td>
<td>Simplicity: less affected by outliers</td>
</tr>
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</table>

Figure 108: Parametric frequency distribution

Figure 109: Parametric and nonparametric distribution characteristics
Statistical resolution or power refers to how well a statistical test can detect differences. Power is determined by data type (i.e., ratio data exceeds interval data, which exceeds ordinal data, which exceeds nominal data). Parametric distributions give better power and resolution than nonparametric distributions, but they make assumptions about the underlying frequency distribution that may or may not be true. This is why you have to understand the data type you are observing and be sure you know what the most likely distribution is for that data. Whenever feasible, you will want to select the highest statistical power possible when analyzing data.

Choosing the appropriate SPC chart

Once different data types are understood, you can look at the different types of statistical process control charts applicable to each data type, as shown in Figure 110. Because interval data are not commonly seen in healthcare improvement projects, the control charts used for this type of data will not be discussed.

The p chart

The p chart ("proportion" chart) is the most common type of control chart in healthcare. It is typically used to look at variation within binary attributes data where there are two possible outcomes (e.g., a defect is present or it is not, a condition is present or it is not). It is used in situations where the sample size is relatively small.

Because the sub-group size can vary, a p chart often shows a proportion of nonconforming observations rather than the actual count. P charts show how the process changes over time. The process attribute (or characteristic) is always described in a binary manner — male/female, yes/no, pass/fail, alive/dead, etc. Because it is possible to set almost anything up as a
proportion, you can often analyze data in this binary form. Examples include the proportion of patients in a specific DRG category, entering a specific hospital, of a particular ethnicity, with a particular infection, developing skin ulcers, or with essentially any complication (other than very rare complications, in which case the g chart is used — see the discussion below). In each case, the proportion represents a “yes/no” situation (either this condition exists or it does not) and is therefore binary.

This type of data generates a binomial frequency distribution, as displayed in Figure 111. A binomial distribution looks like a bell-shaped curve (e.g., like a normal distribution). It can get misleading if the distribution is distorted or “skewed” as it nears its binary limits, 0 or 1. This is more likely to happen when the mean proportion and sample size are small. In this circumstance, a Poisson distribution (c chart) may be more appropriate (see discussion of Poisson distributions and c charts below).

There are four properties that indicate a binomial distribution:

1. There are “n” repeated trials or samplings (e.g., a fixed number of observations).
2. All trials are identical and independent.
3. The probability of success is the same for each observation.
4. Each trial has exactly two possible outcomes, “success” and “failure” — that is, it is binary.

The larger the sample size, the more a binomial distribution will approach a true normal distribution. This type of distribution will generate an SPC chart called an X-bar chart (see discussion of Gaussian distributions below).

The g chart

Most of the other types of SPC charts are uncommonly used in healthcare. The g chart is an exception.
Rare events inherently occur in all kinds of processes. In hospitals, there are adverse drug events, unusual post-operative infections, patient falls, ventilator-associated pneumonias, mortality from community-acquired pneumonia, and other rare, adverse events that cause prolonged hospital stays, result in poor outcomes and increase healthcare costs.

Because rare events occur at very low rates, traditional control charts like the p chart are typically not as effective at detecting changes in the event rates in a timely manner. In these situations, the probability that a given event will occur is so low, considerably larger sample sizes are required to create a p chart and abide by the typical rules governing this type of statistical analysis. In addition to the difficult task of collecting more data, this requires the improvement team to wait far longer to detect a significant shift in the process.

The trouble is that when you are considering very rare events, the statistical power depends more on the actual event rate than on your total sample size (“n”). The effective power depends on the number of events.

The g chart is a statistical process control chart developed by James Benneyan to monitor the number of events between rarely occurring errors or nonconforming incidents in healthcare. The g chart creates a picture of a process over time. Each point represents the number of observed units between occurrences of a relatively rare event. For example, deep mediastinal infections following open heart surgery are very rare (incidence of less than 1 percent). If an improvement team focuses on tracking the number of mediastinal infections, it will take them many years of experience to collect enough cases to have a statistically valid sample. This is also true of other rare events, such as contaminated needle sticks, instances of ventilator associated pneumonia, etc.

To develop a g chart, the team can count and plot the number of non-infection cases occurring between infection cases. This effectively increases the sample size and creates a statistically valid way of analyzing the process. This type of data are summarized with a mean. The “g” in g chart stands for geometric, since data relating to events between occurrences is represented by a geometric distribution, as portrayed in Figure 112.
The g chart helps to display this data in traditional control chart form. Specific formulas for g chart control limits are used with this type of data.

Figure 113 is an example of a g chart illustrating the time between infections in patients receiving total hip replacement. Note the improvement in performance resulting from a change in process (new type of hip prosthesis used).

Figure 114 is an example of a g chart illustrating the time between MRSA infections on a hospital ward as a result of implementing a hand hygiene protocol.

The c chart

It is not uncommon in healthcare to encounter discrete ratio data in the form of “number of per.” Examples include number of children per family, number of tests per patient, number of patients per hour, number of patients through a unit per day, number of blood stream infections per 1,000 central line days and so forth. Data of this type follows a Poisson distribution, as illustrated in Figure 115. When you encounter “number of counts per” data, it always suggests a Poisson distribution.

A Poisson frequency distribution has only one parameter, the mean. With a Poisson distribution, the mean equals the standard deviation.

The control chart that corresponds to a Poisson distribution is the c chart (a “count per unit” chart). If the data are expressed as a proportion, the output is called a u chart (a “unit per proportion” chart). Like other control charts, flipping a Poisson distribution on its side and plotting observations over time will generate a c chart or u chart.
The X-bar chart

Continuous ratio data are the fourth type of data commonly encountered in healthcare. Continuous ratio data are summarized by the mean and standard deviation. This type of data almost always yields a normal (Gaussian or bell-shaped) distribution. If it is a near perfect normal distribution, the chart that works with it is called an X-bar chart.

This type of distribution has more than one parameter. X-bar charts generally have two parallel charts, one for the mean and one for the standard deviation (the two parameters that summarize continuous ratio data). In this format, these are called X-bar and s charts. With an X-bar chart, you typically plot every observation.

What if nothing fits?

There are instances when the data observed in a situation does not easily fit one of the above scenarios. In such situations, the improvement team faces four possible solutions.

1. Transform the data. Many healthcare variables do not meet the assumptions of parametric statistical tests. That is, they are not normally distributed, the variances are not homogenous, or both. These frequency distributions frequently are "skewed" — that is, they have a tail, as portrayed in Figure 116. In this type of skewed
distribution, a normal distribution simply does not fit. To “transform" the data, you can perform a mathematical operation on each observation and then use the transformed numbers in a statistical test. If you are going to use one of these transform methods, you need to have a fairly high degree of certainty that your collected data represents a true, clean process (i.e., not a combination of different processes mixed together).

In these situations, there are several types of mathematical transformations you can perform on the data, including:

- **Log transforms.** This is the most common method for transforming data. You plot the logarithm of each of the data points in the data set. This creates a new frequency distribution that is often a bell-shaped curve, or at least it is less skewed than the initial frequency distribution. When this happens, you can apply parametric tools (e.g., X bar S chart). As a result, patterns in the data become more identifiable and interpretable. Even though you have performed a statistical test on the transformed data, it is not a good idea to report the means, standard errors, or similar results of transformed units. Instead, you need to “back transform” the results by doing the opposite of the mathematical function that was initially used in the data transformation. In a log transformation, a back transform is done by raising 10 to the power of the calculated mean of the logarithmic distribution. The upper and lower control limits, and the individual data points, can be similarly back transformed. While it is good to understand this technique conceptually, it is not necessary to understand the mathematics involved. Suffice it to say that the process has been shown to be mathematically legitimate. Taking this approach does not result in any loss of statistical power.

- **Power transforms.** If a log transform does not work, a “root” or “power” transform can be done. This is generally the third square root of your X’s, the fifth square root of your X’s, or the seventh square root of your X’s. Once again, this process can often transform skewed results into a more normal distribution, allowing you to apply parametric tools. Once these tools have been applied, you need to back transform the data, mean and control limits in a fashion similar to that mentioned under log transforms above. Taking this approach does not result in any loss of statistical power.

- **Use severity of illness transforms.** Technically, severity of illness adjustments can be viewed as a type of transformation. Severity of illness adjustments attempt to eliminate variation arising from differences among patients by breaking a cohort of patients into a series of sub-groups that are relatively homogenous in terms of severity based on a particular measurement parameter (e.g.,
cost per case or risk of mortality). If you break a skewed distribution of patients into severity of illness categories in this fashion, it is not uncommon to find the skewed distribution is actually composed of a series of normal distributions — a normal distribution for each category of severity in the cohort of patients under observation, as seen in Figure 117. You can then do the analysis on each subset of parametric distributions. Once this is done, they can be mathematically rolled back together. You do not lose any statistical power with this approach.

- Linear, cyclic, or nonlinear transforms. There are a variety of other mathematical transformations that can be performed on unusual frequency distributions to enable the application of parametric techniques. A detailed discussion of these methods is beyond the scope of this discussion.

2 Use Shewhart’s method of addressing a non-homogenous sample. Whenever possible, Shewhart sought to convert a data sample into a dataset that would generate a normal distribution to which parametric methods could be applied. In a non-homogenous population, as illustrated in Figure 118, you can randomly draw patients in small groups out of the
total non-homogenous population and create frequency distributions for each of these random groups. If you do this a large number of times (or more accurately, get a computer to do it a large number of times), you can plot averages of small groups of observed values. This generally results in a normal distribution to which you can apply parametric techniques, as shown in Figure 119. Using this approach maintains statistical power. This is an example of the so-called central limit theorem.

3. Use some other known frequency distribution. There are many of these, but most are very esoteric and not pertinent to healthcare except for highly unusual situations.

4. Use a non-parametric control chart — an XmR control chart. The problem with this approach is that you will lose a lot of statistical power. XmR charts provide the lowest level of statistical power. As a result, this is a choice of last resort.

For those involved in clinical and operational improvement, it is not necessary to understand the complicated mathematics behind these methods. You can always get a statistician or a computer to do the computations. However, it is important to understand the rules and techniques at a conceptual level in order to make the appropriate directional decisions when you encounter datasets that require the application of these methods.

There are a number of sources that provide a more detailed discussion of the different types of frequency distributions and their associated SPC charts, as well as their respective uses in healthcare. The interested reader can consult these other sources for additional information.157, 158, 159
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