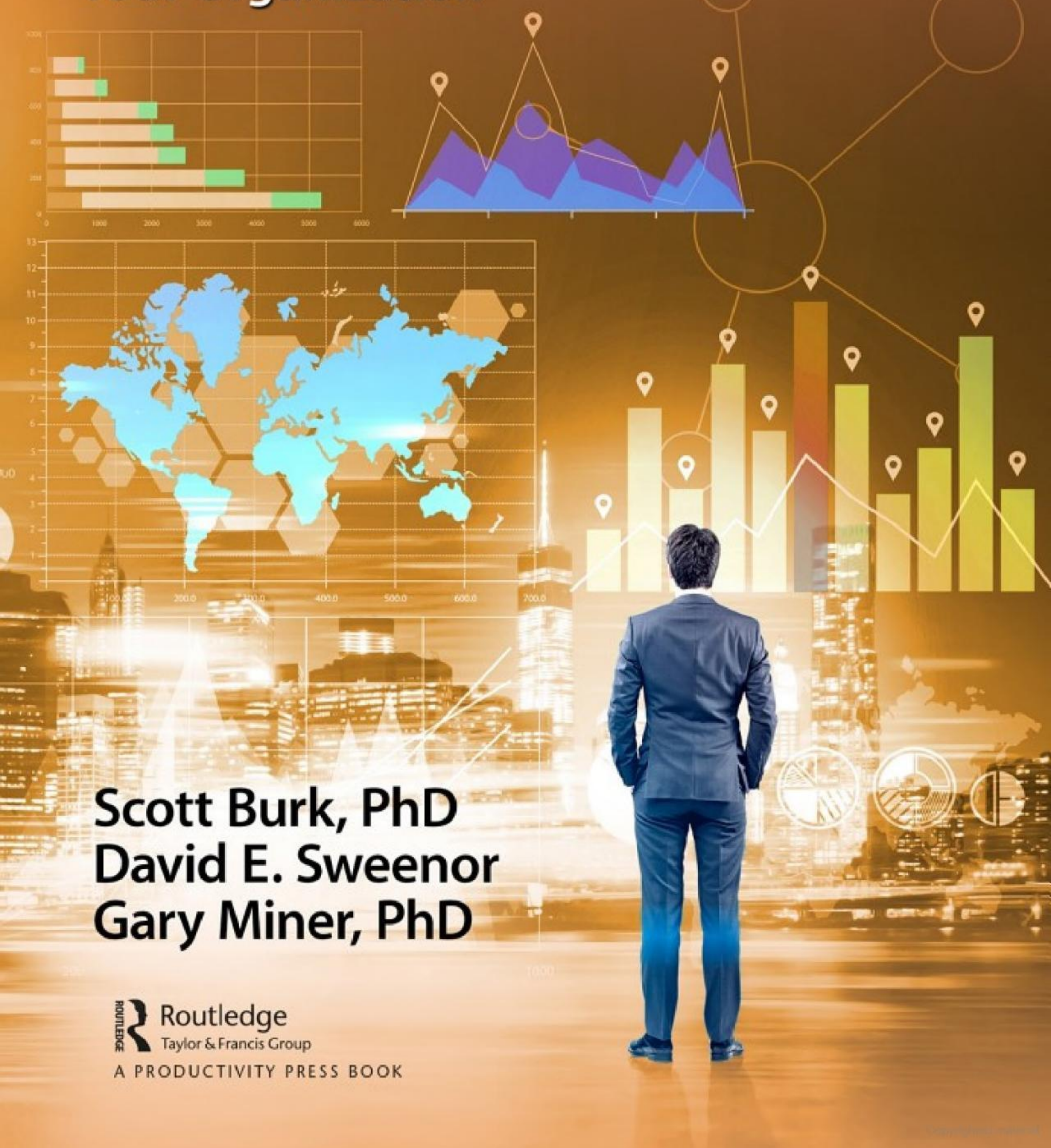
It's All Analytics - Part II

Designing an Integrated AI, Analytics, and Data Science Architecture for Your Organization



Scott Burk, PhD
David E. Sweenor
Gary Miner, PhD

Routledge
Taylor & Francis Group
A PRODUCTIVITY PRESS BOOK

First published 2022
by Routledge
600 Broken Sound Parkway #300, Boca Raton FL, 33487

and by Routledge
2 Park Square, Milton Park, Abingdon, Oxon, OX14 4RN

Routledge is an imprint of the Taylor & Francis Group, an informa business

ISBN: 9780367359713 (hbk)
ISBN: 9781032066813 (pbk)
ISBN: 9780429343957 (ebk)

DOI: 10.4324/9780429343957

Typeset in Garamond
by codeMantra

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Foreword and Tribute to the Authors

This book debunks the common notion that data are the foundation of any analysis. It shows that a much more basic foundation is needed before results of data analysis can be used in an organization effectively – appropriate business processes must be designed and built to accept them. The question is posed early in the book, “We have to change the way we work”? Yes, we must change the way we work. That has happened many times before. It happened during the Industrial Revolution to harness steam power to drive big machines. It happened during the Computer Revolution to move from typewriters to word processors and from paper ledgers to computer databases. This book stands firmly on the 2nd habit proposed by Steven Covey among his *7 Habits of Highly Effective People* – begin with the end in mind. We can’t expect to “force-fit” new solutions into old business practices, any more than ancient people expected to store new wine in old wineskins. Wal-Mart followed this premise by re-engineering its entire business to function as a “business ecosystem”, rather than a bunch of separate systems cobbled together with business process “band-aids”. The System is the starting point, not any element of it. If you dare to read this book, be prepared to learn how to change the entire system in your organization to function as what Bill Gates called the “digital nervous system”. The nerve pulse output of the corporate “brain” must be transmitted effectively through the proper communication channels to move the “muscles” of the organization appropriately to get things done. This happens in biological organisms via the nervous system and the blood stream. The groups of these “business organisms” can work effectively only through proper communication channels orchestrated to permit the entire organization to function as a business ecosystem driven not by steam, and not even by the data themselves, but by analytical products fueled by them.”

Robert Nisbet, PhD
Consulting Data Miner
Goleta (Santa Barbara), California

Preface

More than 70% of corporate analytics efforts fail – even after these corporations have spent very large investments in time, talent, and digital systems. These expenditures were made with anticipation of great returns on investment. It is widely accepted that these projects should return great monetary or corporate benefits. While there are examples of such stories, AI and analytics projects and programs are coming up short. So why do some programs succeed and others fail?

Putting it very simply:

- Companies know they need to invest in AI and analytics.
- Many companies know they should see greater returns on their investments.
- What are the gaps? What is missing in most efforts? What should companies do differently?

This book is about answering those questions and more. It is about covering topics at a level rarely discussed in boardrooms and other books. Yet, these topics need to be understood and addressed.

Why Are Organizations Struggling with Analytics?

For many reasons, we will address those in detail, but let's start with the single biggest problem:

AI and analytics programs are considered something you "add to your business or organization" – a department, some data scientists, some software, and some training. Why doesn't this work? It is not a lack of investment. There is no lack of available tools and platforms in the market. It isn't for lack of trying. Some organizations have been trying to become more data driven for 20 years.

> Well that didn't work, but if we try harder, hire someone smarter to run the department, invest more then surely it will work!

But it doesn't. There are some things that have to be built into the fabric of the business; AI and analytics are one of those things. You might have some success taking an additive or modular approach. However, it will be limited and if your competitors do it more holistically they are going to run circles around you.

You don't need an analytics addition. You don't need an analytics evolution. **You need to reengineer your business around AI and analytics**. The people, the processes, the systems, and the procedures and protocols – all should be parts of this analytics fabric. This is the art and science of the analytics revolution.

One of the most successful corporate paradigm shifts in the United States was the quality revolution. It was only when companies tore out the old business models and paradigms, and then added quality control methods, that they were again able to compete globally. These programs were not short term in nature; they were not add-on programs. They permeated the entire enterprise. Everyone from the cleaning crew to the c-suite was re-educated and forced to adopt their work to a new way of thinking – or exit. It was a necessary mandate; people felt the immediate need to adapt, quickly.

This book is laid out in three parts. Successful analytics programs are built on three cornerstones:

1. Designing and aligning the message of an analytics culture to the people and systems within an organization. Tear down the cultural divide, establish an analytics Center of Excellence, and create an innovation-oriented culture. Understand how decisions should be constructed and made. We present these in Part 1:

   Designing for Organizational Success
2. No organizational plan, educational prowess, or analytics platform can be successful without meaningful data. Data have become complicated and there is much hype about platforms and technologies. We present data architecture considerations at an executive level. We survey data movement, storage, and consumption. Determining the data infrastructure that will be necessary to support all enterprise initiatives for AI and analytics is essential. We present this in Part II:

   Designing for Data Success
3. Determining the AI platforms, functionality, and infrastructure that will be necessary to support all the enterprise initiatives for AI and analytics. Architectural considerations for the data scientist, understanding the differences of academic versus professional practice, and the analytic model maturity framework are all important aspects to success. Is it better to build, buy, or outsource analytics activities? We present this in Part 3:

   Designing for Analytics Technology Success

Some Key Takeaways

1. Understand the importance of culture for analytics success.
2. Understand why organizing people and processes is more important than the budget.
3. Understand the fundamental building blocks of data architectures and how to piece these blocks together for your particular organization.
4. Understand the fundamental building blocks of AI and analytics platforms and how to piece these blocks together for your particular organization.
5. Understanding how AI and analytics are evolving to support changes in society's views are demanding things such as Trustworthy AI, ethics, regulations, and more robust compliance measures.
6. Understand how to scale, sustain, and expand the advances you have made in data and analytics foundations with a meaningful governance infrastructure.

We need an analytics revolution. Be part of it.

Scott Burk
David E. Sweenor
Gary Miner

Authors

Scott Burk has been solving complex business and healthcare problems for 25 years through science, statistics, machine learning, and business acumen. Scott started his career—well actually in analytics—as an analytic chemist after graduating with a double major in biology and chemistry from Texas State University. He continued his education, going to school at night taking advanced courses in science and math at the University of Texas at Dallas (UTD). He then started programming at the toxicology lab where he was working and continued taking computer science (CS) and business courses until he graduated with a master's in business with a concentration in finance soon after from UTD.

Texas Instruments (TI) hired him as a financial systems analyst in its Semiconductor Group, but due to TI's needs and Scott's love of computers, he soon after became a systems analyst for corporate TI. He worked there for 3 years and started itching to get back to school (even though he continued to take courses at night (Operations Research and CS) through TI's generous educational program). TI granted him an educational leave of absence, and he went to Baylor University to teach in the business school and get a PhD in statistics. He joined Baylor as a nontenure track professor teaching quantitative business analysis (today = business analytics).

After graduating, Scott went back to TI as a decision support manager for the consumer arm of TI (today = consulting data scientist). He engaged in many functional areas – marketing and sales, finance, engineering, logistics, customer relations, the call center, and more. It was a dream job, but unfortunately, TI exited that business.

Shortly thereafter, he joined Baylor, Scott & White (BSW) Medical Center, a large integrated healthcare delivery system in Texas, as a consulting statistician. He moved into an executive role as an associate executive director, Information Systems leading data warehousing, business intelligence, and quality organizations working with clinics, hospitals, and the health plan. At the same time, he received a faculty appointment and taught informatics at Texas A&M University. He left, but later came back to Baylor, Scott & White as the chief statistician for BSW Healthplan.

Scott continued his education, getting an advanced management certification from Southern Methodist University (SMU) and master's degree (MS) in data mining (machine learning) from Central Connecticut State University. Scott is a firm believer in life-long learning.

He also worked as the chief statistician at Overstock, reengineering the way they tested and evaluated marketing campaigns and other programs (analytics and statistics). He launched their "total customer value" program. He was a lead pricing scientist (analytics and optimization) for a B2B pricing optimization company (Zilliant) for a number of years. He thoroughly enjoyed working with a rich diverse, well-educated group that affected the way he looks at multidisciplinary methods of solving problems.

He was a risk manager for eBay/PayPal, identifying fraud and other risks on the platform and payment system. He has been working the last few years supporting software development, marketing, and sales, specifically data infrastructure, data science, and analytics platforms for Dell and now TIBCO. He supports his desire to learn and keep current by writing and teaching in the Masters of Data Science Program at City University of New York.

David E. Sweenor is an analytics thought leader, international speaker, and author, and has codeveloped several patents. David has over 20 years of hands-on business analytics experience spanning product marketing, strategy, product development, and data warehousing. He specializes in artificial intelligence, machine learning, data science, business intelligence, the internet of things, and manufacturing analytics.

In his current role as the senior director of product marketing at Alteryx, David is responsible for GTM strategy for the data science and machine learning portfolio. Prior to joining Alteryx, David has served in a variety of roles—including an Analytics Center of Competency solutions consultant, competitive intelligence analyst, semiconductor yield characterization engineer, and various advanced analytics roles for SAS, IBM, TIBCO, Dell, and Quest. David holds a BS in applied physics from Rensselaer Polytechnic Institute in Troy, NY, and an MBA from the University of Vermont.

Follow David on Twitter @DavidSweenor and connect with him on LinkedIn https://www.linkedin.com/in/davidsweenor/.

Gary Miner received his BS from Hamline University, St. Paul, Minnesota, with biology, chemistry, and education majors; MS in zoology and population genetics from the University of Wyoming; and PhD in biochemical genetics from the University of Kansas as the recipient of a NASA Pre-Doctoral Fellowship. During the doctoral study years, he also studied mammalian genetics at The Jackson Laboratory, Bar Harbor, ME, under a College Training Program on an NIH award;

another College Training Program at the Bermuda Biological Station, St. George's West, Bermuda, in a Marine Developmental Embryology Course, on an NSF award; and a third College Training Program held at the University of California, San Diego, at the Molecular Techniques in Developmental Biology Institute, again on an NSF award.

Subsequently he did a postdoctoral in behavioral genetics at the University of Minnesota, where, along with research in schizophrenia and Alzheimer's disease (AD), he learned "how to write books" from assisting the edit of two book manuscripts by his mentor, Irving Gottesman, PhD (Dr. Gottesman returned the favor 41 years later by writing two tutorials for the 2012 book on *Practical Text Mining* book). After academic research and teaching positions, Dr. Miner did another two-year NIH-postdoctoral in psychiatric epidemiology and biostatistics at the University of Iowa, where he became thoroughly immersed in studying affective disorders and AD. All together he spent over 30 years researching and writing papers and books on the genetics of AD (Miner, G.D., Richter, R, Blass, J.P., Valentine, J.L, and Winters-Miner, Linda. *Familial Alzheimer's Disease: Molecular Genetics and Clinical Perspectives*. Dekker: NYC, 1989; and Miner, G.D., Winters-Miner, Linda, Blass, J.P., Richter, R, and Valentine, J.L. *Caring for Alzheimer's Patients: A Guide for Family & Healthcare Providers*. Plenum Press Insight Books: NYC. 1989).

Over the years he has held positions, including professor and department chairman, at various universities including the University of Kansas, The University of Minnesota, Northwest Nazarene University, Eastern Nazarene University, Southern Nazarene University, Oral Roberts University Medical School where he was an associate professor of pharmacology and the director of the Alzheimer Disease & Geriatric Disorders Research Laboratories, and even for a period of time in the 1990s he was a visiting clinical professor of psychology for Geriatrics at the Fuller Graduate School of Psychology & Fuller Theological Seminary in Pasadena, CA.

In 1985 he and his wife Dr. Linda Winters-Miner (author of several tutorials in this book) founded The Familial Alzheimer's Disease Research Foundation (aka "The Alzheimer's Foundation"), which became a leading force in organizing both local and international scientific meetings and thus bringing together all the leaders in the field of genetics of AD from several countries, which then led to the writing of the first scientific book on the genetics of AD. This book included papers by over 100 scientists coming out of the First International Symposium on the Genetics of AD held in Tulsa, OK, in October 1987. During part of this time he was also an affiliate research scientist with the Oklahoma Medical Research Foundation located in Oklahoma City with the University of Oklahoma School of Medicine.

Dr. Miner was influential in bringing all of the world's leading scientists working on genetics of AD together at just the right time when various laboratories from

Harvard to Duke University and University of California-San Diego to the University of Heidelberg, in Germany, and universities in Belgium, France, England, and Perth, Australia, were beginning to find "genes" which they thought were related to AD.

During the 1990s Dr. Miner was appointed to the Oklahoma Governor's Task Force on AD, and also as an associate editor for AD for *The Journal Of Geriatric Psychiatry & Neurology*, which he still serves on to this day. By 1995 most dominantly inherited genes for AD had been discovered, and the one on which Dr. Miner had been working since the mid-1980s with the University of Washington in Seattle—the gene on Chromosome 1 of the human genome—was the last of these initial five to be identified. At that time, having met the goal of finding out some of the genetics of AD, Dr. Miner decided to do something different—to find an area of the business world—and since he had been analyzing data for over 30 years, working for StatSoft, Inc. as a senior statistician and data mining consultant, it seemed to offer a perfect "semi-retirement" career. Interestingly (as his wife had predicted), he discovered that the "business world" was much more fun than the "academic world", and at a KDD-Data Mining meeting in 1999 in San Francisco, he decided that he would specialize in "data mining". Incidentally, he first met Bob Nisbet there who told him, "You just have to meet this bright young rising star John Elder!" and within minutes Bob found and introduced me to John, as he was also at this meeting; thus was born the union that resulted in major, bestselling books, on data mining and predictive analytics being produced during 2009–2018, some in their 2nd editions.

As Gary delved into this new "data mining" field and looked at statistics textbooks in general, he saw the need for "practical statistical books" and started writing chapters and organizing various outlines for different books. Gary, Bob, and John kept running into each other at KDD meetings and eventually at a breakfast meeting in Seattle in August 2005 decided they needed to write a book on data mining. Right then and there they reorganized Gary's outline which eventually became *Handbook of Statistical Analysis and Data Mining Applications*, 2009, published by Elsevier. In 2012, he was the lead author of *Practical Text Mining,* a second book from Elsevier/Academic Press, and in 2015, a third in this "series" *Practical Predictive Analytics* and *Decisioning Systems for Medicine.* All thanks go to Dr. Irving Gottesman, Gary's "mentor in book writing", who planted the seed back in 1970 while Gary was doing a postdoctoral with him at the University of Minnesota.

The second Edition of the 2009 book *Handbook of Statistical Analysis and Data Mining Applications* (https://www.amazon.com/Handbook-Statistical-Analysis-Mining-Applications/dp/0124166326/) was released in 2018, and a book written more for the layperson and decision maker, titled *Healthcare's Out Sick – Predicting A Cure – Solutions That Work*!!!, was released in 2019, published by Routledge/Taylor and Francis Group – "A Productivity Press Book" (https://www.amazon.com/HEALTHCAREs-OUT-SICK-PREDICTING-INNOVATIONS/dp/1138581097).

Dr. Miner is currently working on second and third books in a series with Scott Burk, PhD, along with a 2nd edition of the 2015 “big 1200 page book” on *Practical Predictive Analytics for Medicine*. He also periodically teaches courses on “Predictive Analytics and Healthcare Analytics” for the University of California-Irvine.

I

DESIGNING FOR ORGANIZATIONAL SUCCESS

Chapter 1

Some Say It Starts with Data—It Doesn't

DOI: 10.4324/9780429343957-2

> But where were they going
> Without ever knowing the way?
>
> *The Way, Fastball*

Introduction

The philosopher Aristotle once exclaimed, *horror vacui* – which roughly translates to *nature abhors a vacuum.* In the business world, things are no different. Businesses abhor uncertainty and desire, among other things, stability and predictability. Since the beginning of the COVID pandemic in 2020, business models, norms, and business processes have been severely disrupted – which we have all experienced firsthand. From shortages in critical medicines, medical equipment, facilities, and staffing to not being able to find necessities like food, paper towels, and toilet paper in the supermarket, the impact has been devastating for many.

In order for organizations to build a more resilient business, leaders are accelerating investments in data and analytics technology. Many global business leaders understand that technologies such as artificial intelligence (AI), machine learning (ML), cloud, and data visualization are critical to the success of organizations' strategic goals. Organizations that can redefine themselves and apply appropriate data and analytics technology to their business processes will be rewarded with a sustainable and resilient business. They will also be rewarded with a more predictable and stable future.

Organizations are keenly aware that data continues to be created at unprecedented rates. Business leaders are continually trying to capitalize on this data. But many organizations cannot analyze and act in any meaningful way on the events that create data. Sadly, as soon as data is generated, its information value that can be unlocked from the data begins to decay (Rozsnyai et al., 2009). In order to extract the maximum value and actionable insight from data, it is paramount to ensure that their organizational structure, business processes, and analytics technology are set up for success. What can organizations do to transform disruption into opportunity and align their people, processes, and technology into a competitive weapon?

Organizational Alignment

Start with the End in Mind

In 1989, Stephen R. Covey published the seminal book *The 7 Habits of Highly Effective People*. The second habit noted was to "Begin with the End in Mind" – and analytics and data science are no different. Many organizations are keenly aware that when aligned with business strategy, analytics and data science are critical for a sustainable, resilient, competitive advantage. But at the same time, they often treat it haphazardly and not as a part of the critical business infrastructure, nor do they treat data and analytic processes and output as a core strategic asset.

In order to use AI, analytics, and data science as a competitive weapon, business leaders need to step back and articulate a clear strategic direction for their organization. This business strategy is more than mere hyperbole; they should include strategic goals, business objectives, and key results often referred to as OKRs (objectives and key results). Each of the OKRs may give rise to one or more business initiatives that will be required to achieve those business objectives.

DON'T UNDERESTIMATE THE IMPORTANCE OF CHANGE MANAGEMENT

A recent *Harvard Business Review* article noted that many companies are failing to become data driven despite an increase in technology spending (Bean & Davenport, 2019). The executive survey ("Big Data and AI Executive Survey 2019", 2019) yielded many interesting insights, a few of which are identified below:

- 77% of respondents say that "business adoption" of Big Data and AI initiatives continues to represent a challenge for their organizations.
- Only 7.5% of these executives cite technology as the challenge.
- **93% of respondents identify people and process issues as the obstacle.**
- 40.3% identify lack of organization alignment.
- 24% cite cultural resistance as the leading factors contributing to this lack of business adoption.

Now, entire volumes have been written on change management, and some of the most famous were researched by John P. Kotter (1995). Kotter's book *Leading Change* is widely considered one of the seminal works on change management. Although a detailed treatment of the change management process is beyond the scope of this work, Kotter identified an 8 Step Process for Leading Change (Kotter, 2014) as summarized below:

1. Create a Sense of Urgency
2. Build a Guiding Coalition
3. Form a Strategic Vision and Initiatives
4. Enlist a Volunteer Army
5. Enable Action by Removing Barriers
6. Generate Short-Term Wins
7. Sustain Acceleration
8. Institute Change

It is our hope that when you begin any data or analytic initiative within your business, you keep Kotter's 8 Step Process at the forefront of your discussions. This is one of the most critical elements for ensuring success of data, data science, ML, and AI projects.

In a recent discussion with the Global Head of AI at a global biopharmaceutical company, the following dialogue took place:

David Sweenor: When you consider the data science and ML projects that your team has worked on, what was the primary reason they may not have been successful as you hope? Is it a technology or people and process issue?

Global Head of AI: It's never been a technology issue. In one example, our AI team worked on a project for a year in constant collaboration with the business function that was to receive the application. However, when we went to embed the AI technology in their existing processes, the group manager said, "we have to change how we work?"

In the above dialogue, there was a misalignment between the data science team and business team. Everyone agreed that analytics and data science could help improve the business decisions but the teams did not think through organizational and process changes that would be required. Analytics would substantially change how the business team did their work and they were not quite ready to change their business process nor work behaviors.

To summarize this discussion: As an AI team, you need to be able to hand over the processes and analytic applications you have developed to the corporate project management office who are experienced in change management. The adopting (owning) group may also want to bring in the information technology (IT) team to handle and maintain any IT processes that the AI team developed.

Once the strategic goals, business objectives, OKRs, and business initiatives are established, the leadership and management teams will need to define, map, and prioritize specific projects for each of the initiatives. For the scope of this section, we will primarily limit our discussion to how data and analytics technology can help with those objectives, but other technologies may need to be considered. For example, there may be integration, networking, hardware, devices, applications, infrastructure, security, and other software required for the ultimate solution.

Now that we have prioritized and defined a series of projects to which we can apply data and analytics technology, the organization will then need to establish a cross-functional team to drive the project forward. This team should be composed of all the stakeholders involved in the solution. Some of the roles may include Business Analysts, Project Managers, Organizational Change Managers, IT Professionals, Data Scientists, Software Developers, DevOps Professionals, ML Engineers, Data Engineers, Visualization Experts, App Developers, Integration Specialists, Data and AI Ethicists, Governance Experts, Security Professionals, and so forth. A few of these roles are illustrated in Figure 1.1.

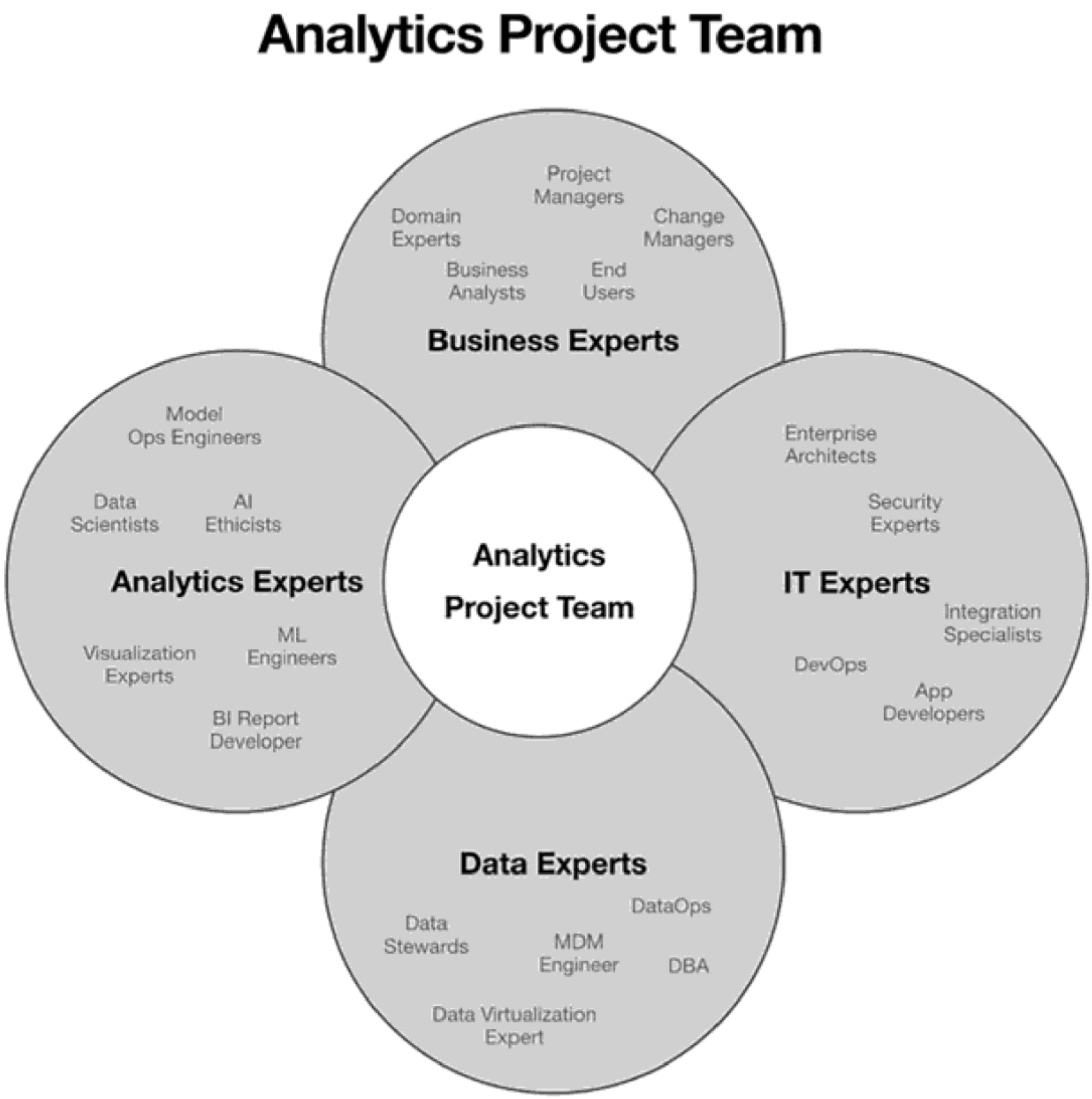

Figure 1.1 Analytics project team – analytics, data, business, and IT roles are required for project success.

One of the most important roles that need to be heavily involved with the cross-functional team is the end users and domain experts. After all, most of these initiatives will require change in how the end users normally conduct their business. If you don't have buy-in from them, you are doomed to fail! Additionally, for each project, we need to ensure that the surrounding functional teams put project management plans and change management plans in place to achieve those objectives. As they say, it takes a village to bring an analytic project to fruition!

HELP! WHERE DO WE START?

Many organizations struggle on where to start with data and analytic initiatives. Industry thought leader Bernard Marr first suggests that businesses need to step back and understand if their business model is still relevant. Marr also recommends that 80% of your data should be used for the organization's biggest challenges, problems, and strategic initiatives. In his book *The Intelligence Revolution: Transforming Your Business with AI* (Marr, 2020) and recent conference talk (Marr, 2020b), Marr identifies the following areas where organizations can use data and analytics.

5 Key Areas Where We Can Use Data and Analytics

1. To improve decision-making within organizations
2. To better understand customers/markets
3. To deliver more intelligent services and products
4. To improve internal business processes
5. Use data as an asset that can be monetized

To get started, Marr suggests that organizations should pick two or three strategic projects and two or three quick wins as initial projects. He also recommends being maniacally focused on customers. Lastly, Marr advises companies to work on Point 5 – *Use data as an asset that can be monetized* after the first four have been addressed.

Each of these projects may require a set of different capabilities to enable their achievement. Recently, the analyst firm Gartner Inc. has brought the notion of "composable apps" (Panetta, 2020) to the forefront of IT and analytics technology discussions. Essentially, "composable apps" are assembled from a set of modular technology building blocks that provide the functionality needed to achieve the stated goal of the application. We like to think of them as Lego blocks. With the right assortment of Legos, you can build almost anything – from cities, to cars, to hospitals, to farms, and to airplanes. These technologies often include integration technology, data management technology, and analytic technology. Data- and analytics-related integration technology is discussed in Chapter 8, data management capability is covered in Part 2, and the analytics capabilities will be discussed in Chapter 10.

In summary to realize the benefits of analytics within the organization, the following elements are a prerequisite:

1. Establish strategic business priorities and OKRs.
2. Define, map, and prioritize specific projects for each of the initiatives.
3. Establish cross-functional teams to understand how technology can help achieve stated business objectives.
4. Establish project management and change management processes and plans.
5. Understand data required to make decision.
6. Understand analytic techniques required to make decision.
7. Partner with end users, domain experts, and business stakeholders and iterate on a solution.
8. Track progress, learn from failures, and celebrate success.

Remove the Cultural Divide and Establish a Center of Excellence

One element that helps to create a sustainable data and analytic culture within an organization is to establish an Analytics Center of Excellence. In the first book, *It's All Analytics* (Burk & Miner, 2020), the authors discussed the different types of organizational structures which included:

- Centerized
- Decentralized
- Matrix or hybrid structures

Now, one important facet of the CoE is the reporting structure within the organization. In the book *Building Analytic Teams* (Thompson, 2020) by John K. Thompson, there is an interesting discussion on the CoE reporting structure. Thompson argues that the best organizational home for the CoE is reporting directly to the Chief Executive Officer (CEO) or the Chief Operating Officer (COO).

When a CoE reports to the CEO, this typically signifies the priority and importance of the CoE to the organization. Also, this would certainly create strong alignment between the organization's strategic objectives and the projects and initiatives that the CoE will undertake. Additionally, this helps with ensuring that the CoE has the appropriate amount of funding and that corporate project management and change management teams are appropriately involved.

Now, realizing that the CEO is extremely busy and may not have the appropriate amount of time to spend with the CoE, Thompson believes that reporting to the COO is the next best option since they have the corporate functions reporting to them. In addition to being able to help marshal the necessary resources for the CoE, they can help facilitate and promote collaboration between the CoE and the various business units as needed.

Now that we have explored the optimal reporting structure for a CoE, where is the worst corporate home for a CoE? We (and Thompson) feel that putting the CoE within an IT organization is probably the worst possible place for them. Why is this the case?

In order to address this, we must understand the differences between how an analytics team operates and how an IT team operates. For a review of the analytic process, please see Chapter 10. If we think about the analytics process, it is iterative in nature and takes a great amount of creativity and innovation to map specific analytic techniques to business problems. As the analytics team attempts to discover, explore, and investigate different analytic approaches, there may be successes and failures. The team will continue to iterate until a suitable approach is found. Then the team will refine and optimize that particular approach.

However, it should be noted that the business processes or decisions that the team is trying to model through mathematics may not be possible for either the analytic team or the decision team. There are many reasons for this which include lack of analytics literacy, lack of patience, lack of clear objectives, and lack of sponsorship. Additionally, one reason may be that the data needed to model the process, system, or behavior is simply not available or may not have been collected. The key point is that the analytics process is creative, iterative, and will have both wins and losses.

Now, if we consider how an IT organization operates, they are typically risk averse and do things in a very structured manner (and for good reason). The creative and interactive elements are, for the most part, nonexistent within an IT organization. So, if an analytics CoE reports to an IT function, they will, over time, pick up and start to emulate the norms and behaviors of the overall function. Additionally, IT management will tend to reward the CoE if they are behaving and acting similar to how the rest of the organization acts. In other words, the analytics CoE will begin to draw up detailed plans, change management processes, and, overall, will be more risk averse compared to if they were not reporting to an IT organization. The two paradigms comparing how an analytics team operates and how an IT team functions couldn't be more diametrically opposed.

I WANT TO BE SMART

Earlier in my career, I (David) worked in a Business Analytics Center of Excellence for a large multinational corporation. The stated goal of the group was to create a shared analytics infrastructure available to any business unit within the organization worldwide. The corporation had hundreds (if not thousands) of disparate servers which hosted various analytics, data science, and business intelligence applications around the globe and many more project teams and end users of that technology around the world. If the organization could decommission the disparate servers, it would result in substantial cost savings.

In addition to helping establish the business architecture of the solution, as a part of the initiative, one of my roles was to help adopting organizations migrate to the shared services (private cloud) model. Obviously, there were many adopting departments (over 120 different project teams upon launch) and business units that simply wanted to migrate their existing analytics and reports to the new infrastructure. Simple enough, we helped them through that process.

As the project progressed, more and more groups wanted to create new business applications on the shared infrastructure. Many of these groups did not have significant experience with business analytics technology at the time so it would begin with a discovery and brainstorming session on what could be possible with data analytics and how it could help them. Interestingly enough, many organizations stated "I wanted our department or business unit to become smarter". I would respond, "I would like to be smarter too. What are you trying to do"? Most of these groups, excited about the analytics technology and its potential, did not have a solid understanding of what they wanted to achieve and accomplish – they just wanted to be smarter.

This is where it would have been helpful to step back and align their objectives to the business strategy and then map and understand how technology (in this case analytics technology) could help support those decisions. Before embarking on any analytic initiative, they need to understand the objectives, goals, and implications of becoming smart. Furthermore, since many of these efforts are truly transformative and will change the way the group operates, they need to understand the commitment required to achieve their objective.

Another interesting aspect of the Business Analytics Center of Excellence was that it reported up through the finance IT organization within the office of the CTO. Relating to our earlier discussion on optimal reporting structures, this may have been suboptimal. An IT organization is very different from how an analytics team should operate.

It has been stated that managing an analytics team is more like managing a team of creative people versus managing a team of IT professionals. An analytics team should be able to test and try different approaches and methodologies, they should be able to iterate rapidly, take risks, be innovative, fail, and learn from these failures. An IT organization is quite the opposite, they are risk averse (for good reason), generally follow strict processes and procedures and want things to run mechanistically.

Innovation-Oriented Cultures

As previously mentioned, analytics is unique from the perspective that there is a certain amount of creativity required and it is iterative. For an organization to move up the analytic maturity curve (see Chapter 10), it needs to understand risks and be receptive to experimentation and the occasional failure or setback. Assuming that the analytic investments are appropriately prioritized, your company can put formal programs together to foster innovation. In fact, here's one such example where an organization used the following process when projects failed:

Steps in this process were (Thompson, 2020):

> To be successful with AI initiatives, organizations need to establish a clear business strategy, start with the end in mind, create cross-functional project teams, promote an innovation-oriented culture, and have the right technology building blocks in place.

1. Acknowledgment of the failure
2. A description of the failure
3. A description of the chance of recovery or remediation
4. A discussion of the best path forward
5. A decision on whether to regroup and work toward obtaining the original objective or to move onto the next challenge
6. Back to action

For anyone who has worked in a manufacturing environment, this is very similar to the plan do check act process.

CoE Team Structure

When designing the team structure, there are two approaches to staffing the CoE team. One approach is to hire full service team members and the other is to hire functionally oriented team members.

Some organizations may staff the team so that each team member can provide "Full Service" capability which means they may work on all of the various tasks and the other approach may be "Functionally Oriented". That is, there may be people who specialize in data pipelines, model building, model deployment, and so forth.

Full Service Team Members

With this approach, a CoE chooses to hire highly experienced data scientists (who tend to be more expensive) that can implement an end-to-end data science and ML solution.

In other words, the data scientist can perform all of the data science and ML steps. The data scientist can:

- Access and integrate data from a wide variety of sources,
- Explore, prepare, and clean the data including:
    - Impute missing values,
    - Remove redundant variables,
    - Understand and handle outliers,
    - Transform variables,
    - Perform data reduction techniques,
    - Creating and selecting meaningful features from the data,
    - Format and put the data in the right shape and format for modeling.
- Create, train, and compare a wide variety of models types.
- Select the winning model for the analytic task at hand.
- Test and deploy the model to the target runtime environment.
- Monitor model performance and retrain, update, and remodel when appropriate.

Much of the literature refers to this type of person as a Data Scientist Unicorn with the insinuation being that unicorns do not exist and no one data scientist can be an expert at all of the steps.

Functionally Oriented Team Members

Functionally oriented approaches are different in that there is generally a team of people working together for the end-to-end process. As an example:

- **Data Engineer** – creates data pipelines for data scientist
- **Data Scientists** – creates data science workflow to prepare data for analytics and create models
- **ML Engineers** – create specialized deep learning ML models and optimize their performance
- **Model Ops Engineers** – create monitoring mechanisms for deployed models and update and retrain and remodel when needed
- **Dev Ops Engineers** – integrate modes within the runtime environment
- **IT professionals** – manage the overall IT infrastructure

Now, in many organizations, it's not so black and white but we hope this gives a sense of the two fundamentally different approaches that one can take.

Data and Analytic Project Team Roles

As previously mentioned, it takes a village to bring an analytics project to fruition. Some of the roles required for a successful data and analytics team include:

- Corporate/Leadership/Governance Roles
    - Chief Analytic Officer/Chief Data Officer
    - Project Manager
    - Change Manager
    - Data and AI Ethicists
    - Governance Experts
    - Security Experts
- Business Roles
    - Business Domain Expert or Subject Matter Expert
    - Business Analyst
- Data Roles
    - Data Engineer
    - Data Steward
    - MDM Engineer
    - Data Virtualization Engineer
    - DBA
- Analytics Roles
    - BI Report Developer
    - Data Scientist
    - ML Engineer
- Hybrid Roles
    - Model Ops Engineer
    - DevOps Engineer
- IT Roles
    - Applications Developer
    - Integration Specialists
    - IT Architect

Now, we recognize that the roles identified above are the different skills that are needed in an "ideal world" and the skills or number of staff may not exist within many organizations. However, we list these roles so that the reader can gain a better sense of the different skills and capabilities that will be needed to bring an analytics project to fruition.

Data and Analytics Literacy

What Is Data Literacy? Data Literacy vs Analytics Literacy

The term data literacy has grown in popularity the last few years. There is no doubt this is a very important concept. In a narrow sense, data literacy has been defined as the ability to read, understand, create, and communicate data as information. With this narrow sense, you need to add "analytics literacy" to this definition to make it useful for any successful business application. That is why we added "analytics literacy" to this section's title. Alternatively, you can use the term data literacy in a broader sense.

For example, Valerie Logan uses the following definition for data literacy (*The Data Lodge*, n.d.):

> The ability to read, write and communicate with data in context and it includes the ability to understand that there's a language around how we are using data in the world. And there's different ways, I call them constructs, for how that language manifests in your work or life. How do you think with data? Like, how do you process with data? How do you engage with other people with data? Like how do you communicate around reports and charts and analytics and artificial intelligence? And finally, how do you apply the outputs of data – how do you make data more useful in your work and in your life.

She adds an important comment on her website (*The Data Lodge*, n.d.):

> Data and analytics are the linchpin of digital transformation, yet culture is the hardest part. Data literacy is the missing link, and the key to cracking the culture code.

First, we will use the broad sense of the term data literacy for the rest of this section; this definition includes analytics literacy in the way Valerie describes it above. Second, we want to focus on the last sentence of her quote. We speak of digital transformation and technology in this book. But, that is not where most AI and analytics programs fail. They fail in "the softer side", the culture. **That is why weaving data literacy inside the culture is so important.**

> When AI and analytics programs fail, it's typically not a technology issue. But rather, the softer side, the culture.

Many mandatory corporate education programs sometimes considered the "flavor of the month program" lack any "sticking power"; they are "one and done". They are not part of the culture. Data literacy will be required for any organization that will survive in the private sector, and stakeholders will demand it in the public sector. Can you imagine an enterprise existing today without computer literacy? No.

Designing the Organization for Program Success

Education is a great place to start, but much more is needed. Education alone will not provide data literacy. You have to make it part of the culture from top to bottom, with patience over a long period of time. It is not the latest corporate initiative. It is a mandate. In the early days of the "computer revolution" when companies started adopting digital technology, there were difficult conversations. Some people that had been valuable had to go because they would or could not adapt. It will be the same in the "AI and analytics revolution". Some will survive, some will not, and some will have to reinvent themselves.

One of the most successful corporate paradigm shifts in the United States was the quality revolution. As global markets opened in the 70s and 80s it was clear that the United States had major problems. The quality of goods produced outside the United States were cheaper and superior. Market share was drastically dropping. Through programs initiated in the late 80s and 90s US quality rose and made up the gaps. A prime example was the Total Quality Management Program (TQM) introduced by Edward R. Deming (see "Additional Resources" at the end of this chapter). According to (Ciampa, 1996):

> **TQM** consists of organization-wide efforts to install and make permanent climate where employees continuously improve their ability to provide on demand products and services that customers will find of particular value. **"Total"** emphasizes that departments in addition to production (for example sales and marketing, accounting and finance, engineering and design) are obligated to improve their operations; **"Management"** emphasizes that executives are obligated to actively manage quality through funding, training, staffing, and goal setting. While there is no widely agreed-upon approach, TQM efforts typically draw heavily on the previously developed tools and techniques of quality control.
>
> (Emphasis added)

These programs were not short term in nature, they permeated the entire enterprise (Scott (author) was at Texas Instruments in the 90s and can attest to the success of these programs, stock in 1990 was $2, on 1/21/21 it was $175).

These quality programs have not gone away, they have morphed into new programs built on many of the same paradigms, just adapted for new pressures, technology, and changes organizations are facing.

Organizations that want to succeed with analytics should:

1. Commit at the highest level in the organization.
2. Commit to the long term. This is the long game.

3. Think carefully and strategically about their industry, their position in the industry, and how they can effectively compete with AI and Analytics.
4. Determine the role of analytics in every function of the organization.
5. Communicate the what, why, and how across the entire organization.
6. Commit to educate and support staff by role and individual responsibility.
7. Commit to change processes (where it makes sense) based on augmented decision-making and automation. Do not change process just to change process, but most can benefit with some form of a data-driven approach.
8. Support, reeducate, retrain, and relocate staff whenever possible. But, be willing to lose staff by attrition or cut staff if they cannot commit to the new culture.
9. Stay the course. Reiterate and adjust where necessary.

This is **designing and aligning** the organization for program success. The final step is execution.

Analytics Success Involves More than Technology

People and Process – Not Merely Technology

Organizations want to be data driven. They know that the right investments can set them apart in a very competitive and evolving world, and thus these organizations are accelerating investments in AI technology.

However, *leading corporations are failing in their efforts to become* "data driven" (Bean & Davenport, 2019). A survey conducted by NewVantage Partners polled very large corporations such as American Express, Ford Motor, General Electric, General Motors, and Johnson & Johnson. Results of the survey ("Big Data and AI Executive Survey 2019", 2019) included the following statistics:

- % of survey participants report that they **have yet to forge a data culture.**
- % report that they have **not created a data-driven organization.**
- % state that they are **not yet treating data as a business asset.**
- % admit that they are not competing on data and analytics.
- Further, the percentage of firms identifying themselves as being data driven **had declined in each of the past 3 years** – from 37.1% in 2017 to 32.4% in 2018 to 31.0% in 2019.

Why?

Because investments in technology and infrastructure is the easy part! The hard part **is a commitment to process, people, and culture**! Note the bolded bullets above. These gaps are not in technology. They are gaps in culture. Gaps in alignment of people and strategy – data and analytics literacy, we just discussed. It is *Design and Align* and that includes people, process, and technology.

You must tackle the hard part to gain all the rewards. **You must commit to the Analytics Revolution and that means a shift in culture.** Just as enterprises and agencies had to adapt to the computer revolution, major companies had to adapt to the quality revolution. Organizations now have to adapt to the analytics revolution or be wiped out.

Ethics

Analytics also starts with doing the right thing. Now, more than ever, employees want to be part of organizations that do not merely meet narrow needs of boards, elected officials, or investors; employees want more. They want to be part of organizations that are socially responsible and organizations that have a positive corporate social impact (see gray box, Millennials Have High Expectations). You cannot be socially responsible without ethics; it is a necessary condition. It does not ensure social responsibility. But it is virtually impossible to be socially responsible without ethics.

Ethical concerns are mentioned in several chapters of the book. We specifically address concerns in Chapter 3. We also address corporate responsibilities of analytics and data.

Millennials Have High Expectations for the Actions of Business When It Comes to Social Purpose and Accountability

For example, a 2016 Cone Communications study reveals:

- 75% of millennials would take a pay cut to work for a socially responsible company.
- 76% of millennials consider a company's social and environmental commitments before deciding where to work.
- 64% of millennials won't take a job if a potential employer doesn't have strong corporate responsibility practices.

According to a PricewaterhouseCoopers report titled "Millennials at work – Reshaping the workplace", corporate social values become more important to millennials when choosing an employer once their basic needs, like adequate pay and working conditions, are met. The report states that "millennials want their work to have a purpose, to contribute something to the world and they want to be proud of their employer".

Governance

Governance is sometimes undervalued by people outside of IT or a direct governance function. However, it is critical and should be part of the data literacy program to educate the importance and various roles of governance. It isn't about making jobs harder. It is about sustainability more than anything else. It is about securing and sustaining investments. If you are going to spend millions of dollars on people and technology you need a multi-tier governance strategy. You need human resource governance, data governance, and AI and analytics governance as part of a corporate governance umbrella.

Technology

Data and Analytics Platform Service Areas

In order for data and analytics platforms to effectively serve the business, the organization needs to consider the various domains that the platform needs to support. Broadly speaking, they will generally span four different functional areas: Enterprise Systems, Customer Experience Systems, IoT (Internet of Things) Platform, and Partner Ecosystems (Swanton, 2018) as illustrated in Figure 1.2.

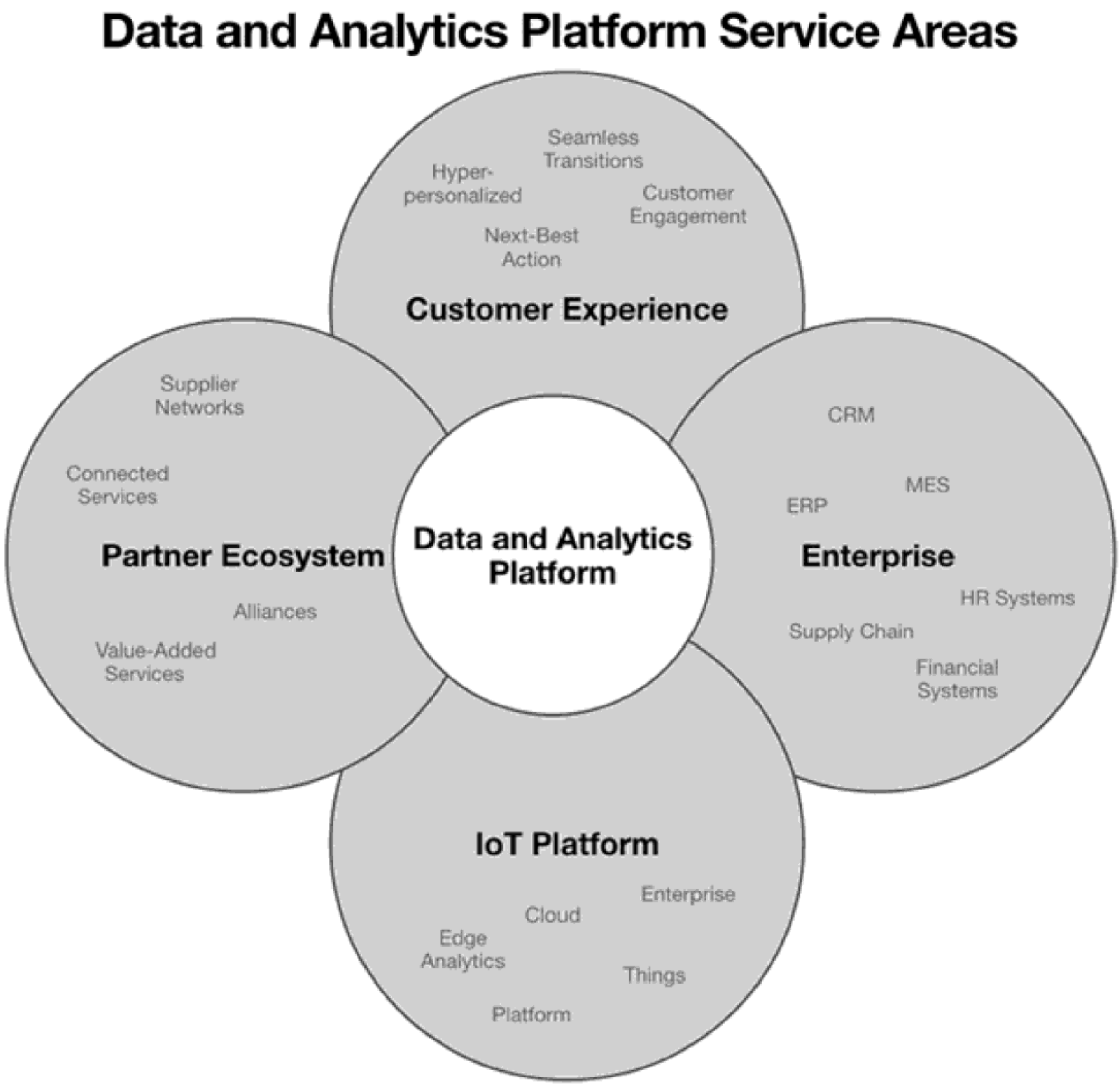

Figure 1.2 Data and analytics platform service areas.

Data and Analytics Architecture

To effectively meet the needs of Customer Experience, Partner Ecosystems, IoT Platforms, and the Enterprise, organizations need a robust data and analytics architecture. Figure 1.3 identifies some of the common components that will be in the data and analytics architecture. These functional areas span data management, analytics, and deployment of those analytic pipelines into business systems. Many of the data-related technologies will be discussed in Part 2 and analytics technology will be discussed in Part 3.

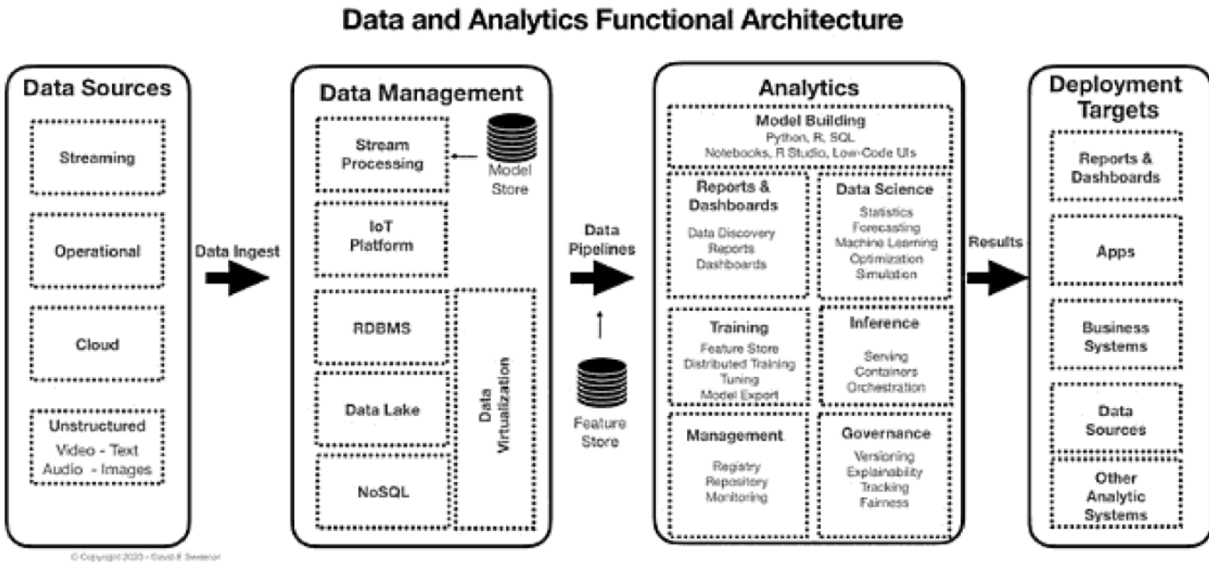

Figure 1.3 Data and analytics functional architecture.

Summary

It is important to start with the end in mind when beginning any data and analytic initiative. Organizations need to understand the business decision to be made and then work backward from that. Then, to improve your odds of success, we recommend that organizations establish an analytics CoE and staff the CoE.

After the organization is aligned and committed to data and analytics, we discussed the importance of data and analytic literacy. We then briefly discussed the importance of people and processes as well as ethics and governance. Lastly, we discussed the service areas for data and analytics platforms as well as the components of the data and analytics architecture.

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Additional Resources

Valerie Logan is on a mission to expand data/analytics literacy. She has participated in many webinars, podcasts, and events which are easy to find. Her website is https://www.thedatalodge.com/.

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W. Edwards Deming was a foundational figure. There are dozens of books written by him or about him and everything we have experienced is worth reading. You can also find useful videos of his lessons such as those referring to 'The Red Bead Experiment' or 'Lessons from the Read Bead Experiment'. You can also check out the W. Edwards Deming Institute, https://deming.org/. Two seminal books to consider are, *The New Economics for Industry, Government, Education* (1991) by Deming and *The Essential Deming: Leadership Principles from the Father of Quality* (2012) by W. Edwards Deming, Joyce Orsini, and Diana Deming Cahill.

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Chapter 2

The Anatomy of a Business Decision

DOI: 10.4324/9780429343957-3

> Be wise today so you don't cry tomorrow.
>
> **E.A. Bucchianeri**

The Anatomy of a Business Decision

Before we can understand how a business decision is made, it is important to understand how a business works. From a very high level, any business, corporation, or government is composed of a number of functional areas and departments. These different functional areas execute various business processes that are designed to achieve a specific set of tasks in support of organizational goals.

Some of these functional areas are identified below:

- Administration
- Clinical and Inpatient Operations
- Continuum of Care
- Pharmacy and Pharmacy Administration
- Bed and Resource Management
- Claims Processing
- Finance and Accounting
- Human Resources
- Production and Quality Control
- Research and Development
- Sales and Marketing
- Supply Chain and Distribution
- Service and Support

Now, each of these functional areas has a series of business processes associated with it. As an example, business process may include:

- Quote to Cash
- Care Coordination

- Prior Authorization
- Patient Admissions
- Patient Scheduling
- Collections
- Eligibility and Coverage
- Bed Management
- Procure to Pay
- Employee Hiring and Onboarding
- Customer Service
- Shipping
- Fraud Detection

Each of these processes consists of a sequence of steps. Some of these steps may be automated while some may be manual. If one thinks of a business as a sequence of steps, each step at its most basic level can be thought of as "proceed to next step", "do this", or "do that".

This implies that there can be hundreds, thousands, or millions of tiny decisions that can be made in a business each day. Each one of these decisions may be able to be augmented with data and analytics to make a smarter decision.

It is imperative that the project teams really understand the processes within their organization and how decisions get made. By some estimates, it has been estimated that "Managers at a typical Fortune 500 company may waste more than 500,000 days a year on ineffective decision making" (Smet et al., 2019).

> "Managers at a typical Fortune 500 company may waste more than 500,000 days a year on ineffective decision making". (Smet et al., 2019)

There are a myriad of reasons but if data and analytics can help improve and optimize even a small portion of the decisions within an organization, the benefits could be enormous.

What Is a Business Decision?

Now within an organization, there are different types of decisions that can be made which include strategic, tactical, and operational which will be discussed in the next section. When data and analytics are used to help make or inform decisions, we often refer to these as "digital decisions". To use data and analytics to make a decision, it is useful to think of this as a flow as illustrated in Figure 2.1

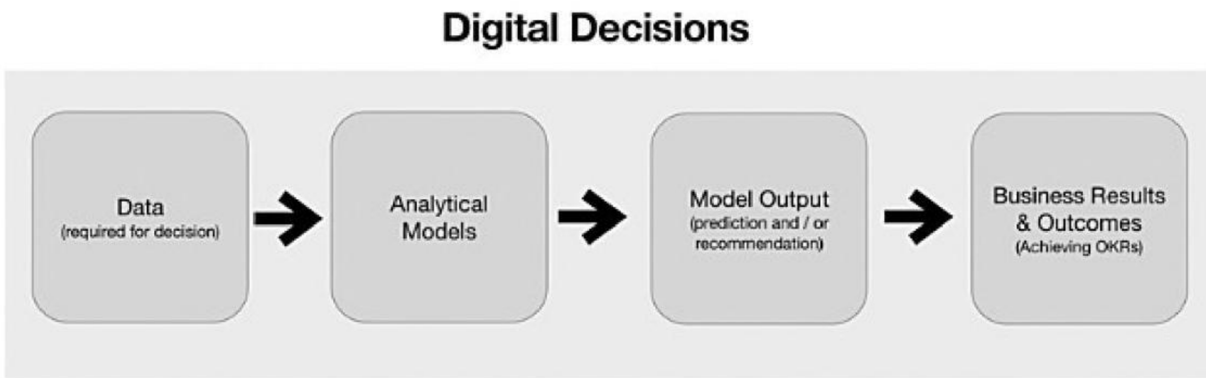

Figure 2.1 Conceptual flow for business decision.

To expand on this a bit, we can look at Figure 2.2 (adapted from Siegel, 2013) that illustrates how predictive analytics can be used to make a decision.

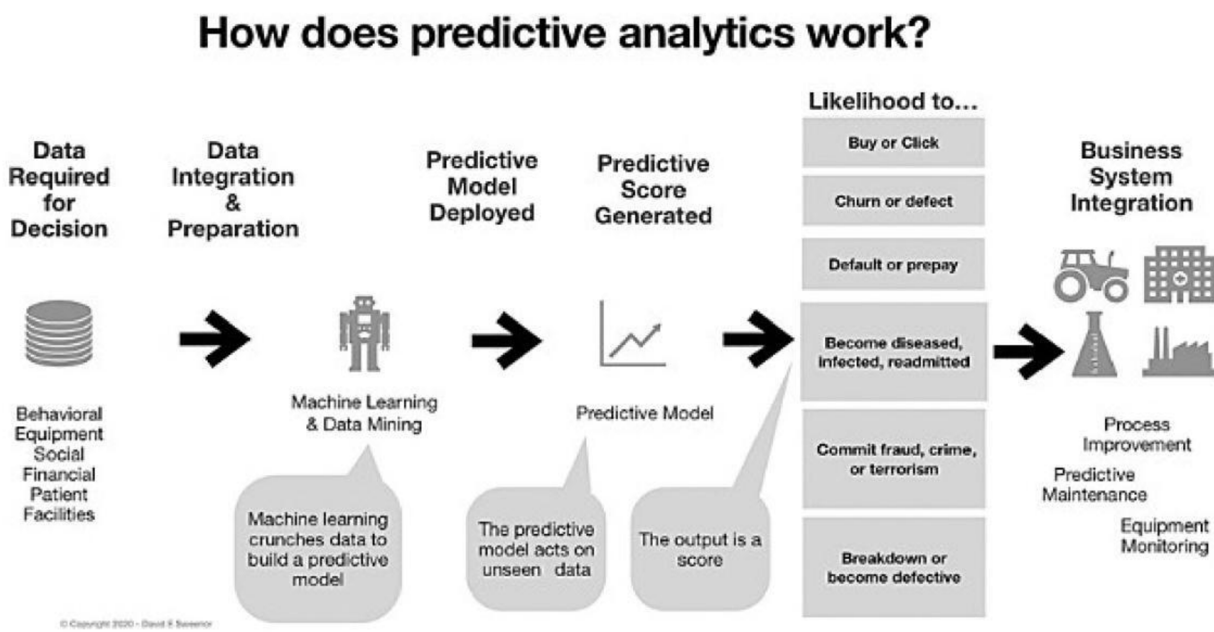

Figure 2.2 Example of predictive analytics in action.

In the example above, input data is accessed and aggregated from disparate data sources. After the data is aggregated and prepared for analytics, models are created; these can be statistical models, data science models, optimization models, forecasting models, machine learning models, or a combination of models, all created from the input data (please note, the training and testing phases of modeling are not illustrated above). Next, a predictive model (formula) is then applied to new data the model has never seen before. Subsequently, the output of this is oftentimes a score which is a probability that something will happen: The probability that someone will buy or click something on the website, that someone may become diseased, infected, or readmitted, or that a machine could break down or become defective. The output score is then generally embedded into a business process or application.

Now that we have a good understanding of how data and analytics work and how they can potentially be used to improve business decisions, it is important to have a basic understanding on the potential value of a business decision that is informed by a predictive analytic output.

The Value of a Decision Which Uses Data and Analytics?

Now that we have a sense for how analytics are used to make decisions, how can that impact the bottom line? Figure 2.3 below adapted from Siegel (2013) represents the flow for a direct mail campaign.

Figure 2.3 The value of a decision before analytics.

Before Analytics

Assume that it takes $2 to mail a holiday catalog to each prospect on our mailing list and 1 out of every 100 responses will buy an item from the catalog. Further assume that we make $220 for each response. Now, if we mail the catalog to one million prospects, we will make $200,000 in profit. Not bad, huh?

After Analytics

Now, given the same assumptions as above, let's further assume that the output of our analytical model suggests that 25% of the entire database of 1 M potential customers are three times more likely to respond. This means that now, we only have to mail the catalog to 250K prospects. Given the same scenario, after some quick math, we see that our profit jumps from $200,000 to $1,150,000 which represents a 5.75 × improvement. I'd take that prediction any day. This is illustrated in Figure 2.4.

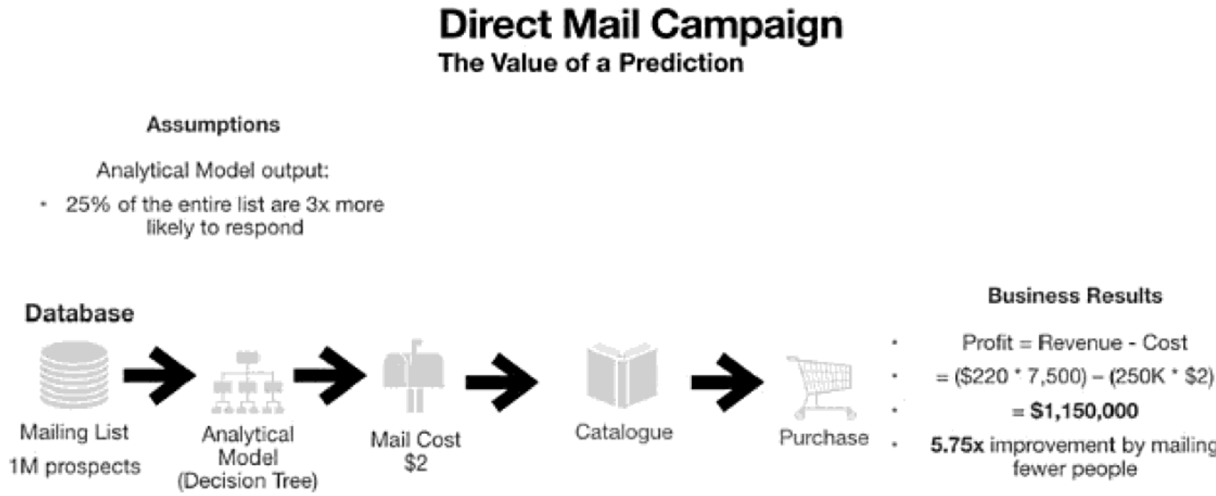

Figure 2.4 The value of a decision after analytics, a 5.75× improvement!

Case Study: The Power of a Healthcare Prediction

Surgical site infections (SSIs) are the one of the leading and most costly types of hospital-acquired infections. In fact, it is estimated that 2 million patients have these infections and 90,000 are expected to die. It is estimated that costs associated with these infections range from $28 billion to $45 billion in the United States alone (Stone, 2009). For an individual patient, the cost of a hospital-acquired infection can increase the total hospital cost by over $20,000 (Surgical Site Infection, 2019), (Gbegnon et al., n.d.). This makes it extremely important for healthcare providers to do everything they can to reduce the risk of these infections. At the University of Iowa, they have taken a novel approach and used predictive analytics to reduce these risks.

The University of Iowa Hospitals and Clinics has created a predictive model to predict the likelihood of a surgical site infection (Gbegnon et al., n.d.). The model uses data from EPIC (the healthcare record), insurance data, and real-time data collected during the surgery.

Similar to our fictitious catalog mailing example above, the following assumptions were made (Gbegnon et al., n.d.):

Assumptions:

- Consider negative pressure wound therapy
- 60%–80% effective at reducing SSI in high-risk wounds
- Total cost approximately $1,500
- We can address 64% of SSI by using therapy in ⅓ of patients

For this specific scenario, the cost of an SSI was estimated to be $28,000 per patient and the cost of intervention was approximately $500. Financially