



# ENTERPRISE ANALYTICS

Optimize Performance, Process, and  
Decisions through Big Data



EDITED BY  
**THOMAS DAVENPORT**

# Enterprise Analytics

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# Enterprise Analytics

Optimize Performance, Process,  
and Decisions Through Big Data

Thomas H. Davenport

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# Foreword and Acknowledgments

The collection of research in this book personifies the contributions of a group of people who have made the International Institute for Analytics the success it is today. This book is the result of three cups of hard work, two cups of perseverance, and a pinch of serendipity that got our fledgling company started.

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This book is also a credit to the perseverance of two great talents within IIA. Katherine Busey was IIA's first employee in Boston and was the person who helped convince Jeanne Glasser at Pearson that IIA's research deserved to be read by more than just our research clients. Thanks as well to Callie Youssi, who coordinates all of IIA's faculty research activities, which is no simple task.

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**Jack Phillips**

Chief Executive Officer, International Institute for Analytics

# About the Authors

**Thomas H. Davenport** is co-founder and research director of IIA, a Visiting Professor at Harvard Business School, Distinguished Professor at Babson College, and a Senior Advisor to Deloitte Analytics. Voted the third leading business-strategy analyst (just behind Peter Drucker and Tom Friedman) in *Optimize* magazine, Davenport is a world-renowned thought leader who has helped hundreds of companies revitalize their management practices. His Competing on Analytics idea recently was named by *Harvard Business Review* one of the 12 most important management ideas of the past decade. The related article was named one of the ten must-read articles in *HBR's* 75-year history. Published in February 2010, Davenport's related book, *Analytics at Work: Smarter Decisions, Better Results*, was named one of the top 15 must-reads for 2010 by *CIO Insight*.

**Elizabeth Craig** is a research fellow with the Accenture Institute for High Performance in Boston. She is the coauthor, with Peter Cheese and Robert J. Thomas, of *The Talent-Powered Organization* (Kogan Page, 2007).

**Jeanne G. Harris** is a senior executive research fellow with the Accenture Institute for High Performance in Chicago. She is coauthor, with Thomas H. Davenport and Robert Morison, of *Analytics at Work: Smarter Decisions, Better Results* (Harvard Business Press, 2010). She also cowrote the 2007 book *Competing on Analytics: The New Science of Winning* (also from Harvard Business Press).

**Robert Morison** serves as lead faculty for the Enterprise Research Subscription of IIA. He is an accomplished business researcher, writer, discussion leader, and management consultant. He is coauthor of *Analytics at Work: Smarter Decisions, Better Results* (Harvard Business Press, 2010), *Workforce Crisis: How to Beat the Coming Shortage of Skills and Talent* (Harvard Business Press, 2006), and three *Harvard Business Review* articles, one of which received a McKinsey Award as best article of 2004. He has spoken before scores of corporate, industry, and government groups and has been a commentator on workforce issues on *Nightly Business Report* on PBS. Most recently executive vice president and director of research with

nGenera Corporation, he earlier held management positions with the Concoors Group, CSC Index, and General Electric Information Services Company.

**Dr. Keri E. Pearson** is an expert in the area of managing and using information. She has worked with CIOs and executives from some of the largest corporations in the world. She has expertise in helping executives create strategies to become Web 2.0-enabled enterprises, designing and delivering executive leadership programs, and managing multiclient programs on issues of interest to senior executives of information systems. She specializes in helping IT executives prepare to participate in the strategy formulation processes with their executive peers. She's a faculty member of the International Institute for Analytics and the Founding Partner and President of KP Partners, a CIO advisory services firm.

**Bill Franks** is a faculty member of the International Institute for Analytics and is Chief Analytics Officer for Teradata's global alliance programs. He also oversees the Business Analytic Innovation Center, which is jointly sponsored by Teradata and SAS; it focuses on helping clients pursue innovative analytics. In addition, Bill works to help determine the right strategies and positioning for Teradata in the advanced analytics space. He is the author of the book *Taming the Big Data Tidal Wave* (John Wiley & Sons, Inc., April, 2012, [www.tamingthebigdatatidalwave.com](http://www.tamingthebigdatatidalwave.com)).

**Eric T. Peterson** is a faculty member of the International Institute for Analytics. He is the founder of Web Analytics Demystified and has worked in web analytics for over 10 years as a practitioner, consultant, and analyst. He is the author of three best-selling web analytics books: *Web Analytics Demystified*, *Web Site Measurement Hacks*, and *The Big Book of Key Performance Indicators*. He is one of the most widely read web analytics writers at [www.webanalyticsdemystified.com](http://www.webanalyticsdemystified.com).

**John Lucker** is a principal with Deloitte Consulting LLP, where he leads Deloitte's Advanced Analytics and Modeling practice, one of the leading analytics groups in the professional services industry. He has vast experience in the areas of advanced analytics, predictive modeling, data mining, scoring and rules engines, and numerous other advanced analytics business solution approaches.

**James Taylor** is a faculty member of the International Institute for Analytics and is CEO of Decision Management Solutions. Decision Management Systems apply business rules, predictive analytics, and optimization technologies to address the toughest issues facing businesses today, changing how organizations do business. He has over 20 years of experience in developing software and solutions for clients. He has led Decision Management efforts for leading companies in insurance, banking, health management, and telecommunications.

**Stacy Blanchard** is the Organization Effectiveness Services and Human Capital Analytics lead for Accenture Analytics. With over 15 years of experience in aligning strategy, culture, and leadership for organizations, she has worked globally across a multitude of client situations and industries. She integrates real-world experience with recognized approaches to coach and align the C-suite to drive transformational agendas. Prior to Accenture, she was the CEO of Hagberg Consulting Group, an organization consultancy specializing in the assessment, alignment, and transformation of strategy, corporate culture, and leadership.

**Carl Schleyer** is Director of Operations and Analytics for Sears Holdings Corporation (an IIA sponsor) and is responsible for gathering and analyzing large volumes of data in order to support talent and human capital strategies and tactics. As a part of this role, Carl created the first analytical team dedicated to purely human capital pursuits within Sears Holdings. His passion is unlocking the value of data through influencing decisions. Carl is a 20+ year veteran of the retail industry, having served various functions within HR.

**Leandro DalleMule** is Senior Director for Global Analytics at CitiGroup. Prior to this, he was a Senior Manager for Deloitte's analytics consulting practice, a risk manager for GE Capital, and a brand manager for Exxon in Brazil.

**Callie Youssi** is Vice President of Research Operations for the International Institute for Analytics. In this role, she works to build, manage, and support IIA's global faculty as they uncover the most compelling applications of analytics. She is responsible for aggregating and analyzing the areas of greatest interest to IIA clients and ensuring a strong faculty bench to address those focus areas.

**Katherine Busey** is Vice President of Business Development for the International Institute for Analytics. In this role, she is responsible for developing global business opportunities for IIA. She works with IIA's underwriters, partners, and research clients to uncover new trends in the analytics space and bring together vendors and practitioners.

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# Introduction: The New World of Enterprise Analytics

*Thomas H. Davenport*

## **The Rise of Analytics**

Analytics aren't new—I've found references to corporate analytical groups as far back as 1954—but they seem to be more important to business and organizational life than ever before. Analytical approaches to decision-making and management are on the rise because of several factors:

- The dramatic increase in the amounts of data to analyze from various business information systems
- Powerful and inexpensive computers and software that can analyze all this data
- The movement of quantitatively trained managers into positions of responsibility within organizations
- The need to differentiate products and offers, optimize prices and inventories, and understand what drives various aspects of business performance

As a result, many factors indicate that analytical initiatives, jobs, and organizations are taking off around the world. According to LinkedIn data, for example, the number of people starting analytics or data scientist jobs increased tenfold from 1990 to 2010. Every major consulting firm has developed an analytics practice. According

to Google Trends, the number of searches using the term “analytics” increased more than twenty-fold between 2005 and 2012; searches for the term “big data” (defined in a moment) showed an even more dramatic rise beginning in 2010. The current era has been described as the “Age of Analytics,” the “Age of Algorithms,” and the “Moneyball Era,” after the book and movie about the application of analytics to professional baseball.

## Enterprise Analytics

One important attribute of the increased focus on analytics is that it has become—at least for many organizations—an “enterprise” resource. That is, instead of being sequestered into several small pockets of an organization—market research or actuarial or quality management—analytical capabilities are being recognized as something that can benefit an entire organization. Diverse groups are being centralized, or at least coordination and communication are taking place between them. Analytical talent is being inventoried and assessed across the organization. Plans, initiatives, and priorities are being determined by enterprise-level groups, and the goal is to maximize the impact on the enterprise.

Hence the title of this book. Many of the chapters relate to how analytics can and should be managed at an enterprise level. If there were a set of guidelines for a Chief Analytics Officer—and some people in this role are emerging, albeit still in relatively small numbers—this book would provide many of them. We are not yet at the point where analytics is a broadly recognized business function, but we are clearly moving in that direction.

## The Rise of “Big Data”

Excitement about analytics has been augmented by even more excitement about *big data*. The concept refers to data that is either too voluminous or too unstructured to be managed and analyzed through traditional means. The definition is clearly a relative one that

will change over time. Currently, “too voluminous” typically means databases or data flows in petabytes (1,000 terabytes); Google, for example, processes about 24 petabytes of data per day. “Too unstructured” generally means that the data isn’t easily put into the traditional rows and columns of conventional databases.

Examples of big data include a massive amount of online information, including clickstream data from the Web and social media content (tweets, blogs, wall postings). Big data also incorporates video data from retail and crime/intelligence environments, or rendering of video entertainment. It includes voice data from call centers and intelligence interventions. In the life sciences, it includes genomic and proteomic data from biological research and medicine.

Many IT vendors and solutions providers, and some of their customers, treat the term as just another buzzword for analytics, or for managing and analyzing data to better understand the business. But there is more than vendor hype; there are considerable business benefits from being able to analyze big data on a consistent basis.

Companies that excel at big data will be able to use other new technologies, such as ubiquitous sensors and the “Internet of things.” Virtually every mechanical or electronic device can leave a trail that describes its performance, location, or state. These devices, and the people who use them, communicate through the Internet—which leads to another vast data source. When all these bits are combined with those from other media—wireless and wired telephony, cable, satellite, and so forth—the future of data appears even bigger.

Companies that employ these tools will ultimately be able to understand their business environment at the most granular level and adapt to it rapidly. They’ll be able to differentiate commodity products and services by monitoring and analyzing usage patterns. And in the life sciences, of course, effective use of big data can yield cures to the most threatening diseases.

Big data and analytics based on it promise to change virtually every industry and business function over the next decade. Organizations that get started early with big data can gain a significant competitive edge. Just as early analytical competitors in the “small data” era (including Capital One bank, Progressive insurance, and Marriott hotels) moved out ahead of their competitors and built a

sizable competitive edge, the time is now for firms to seize the big-data opportunity.

The availability of all this data means that virtually every business or organizational activity can be viewed as a big-data problem or initiative. Manufacturing, in which most machines already have one or more microprocessors, is already a big-data situation. Consumer marketing, with myriad customer touchpoints and clickstreams, is already a big-data problem. Governments have begun to recognize that they sit on enormous collections of data that wait to be analyzed. Google has even described the self-driving car as a big data problem.

This book is based primarily on small-data analytics, but occasionally it refers to big data, data scientists, and other issues related to the topic. Certainly many of the ideas from traditional analytics are highly relevant to big-data analytics as well.

## **IIA and the Research for This Book**

I have been doing research on analytics for the last fifteen years or so. In 2010 Jack Phillips, an information industry entrepreneur, and I cofounded the International Institute for Analytics (IIA). This still-young organization was launched as a research and advisory service for vendors and users of analytics and analytical technologies. I had previously led sponsored research programs on analytics, and I knew they were a great way to generate relevant research content.

The earliest support for the Institute came from the leading analytics vendor SAS. We also worked with key partners of SAS, including Intel, Accenture, and Teradata. A bit later, other key vendors, including SAP and Dell, became sponsors of IIA. The sponsors of IIA provided not only financial support for the research, but also researchers and thought leaders in analytics who served as IIA faculty.

After recruiting other faculty with academic or independent consulting backgrounds, we began producing research outputs. You'll see several examples of the research outputs in this book. The IIA produced three types of outputs: research briefs (typically three-to-five-page documents on particular analytics topics); leading-practice briefs (case studies on firms with leading or typical analytical issues);

and write-ups of meetings, webcasts, and audioconferences. The emphasis was on short, digestible documents, although in some cases more than one brief or document has been combined to make one chapter in this book.

With some initial research in hand, we began recruiting corporate or organizational participants in IIA. Our initial approach was to focus on general “enterprise” topics—how to organize analytics, technology architectures for analytics, and so forth. We did find a good reaction to these topics, many of which are covered in this book. Practitioner companies and individual members began to join IIA in substantial numbers.

However, the strongest response was to our idea for industry-specific research. Companies seemed quite interested in general materials about analytical best practices but were even more interested in how to employ analytics in health care or retail, our first two industry-specific programs. That research is not featured in this book—we may do other books on analytics within specific industries—but we did include some of the leading-practice briefs from those industries as chapters.

## **The Structure of This Book**

All the chapters in this book were produced in or derived from IIA projects. All the authors (or at least one author of each chapter) are IIA faculty members. A few topics have appeared in a similar (but not exactly the same) form in journal articles or books, but most have not been published outside of IIA. The chapters describe several broad topics. Part I is an overview of analytics and its value. Part II discusses applying analytics. Part III covers technologies for analytics. Part IV describes the human side of analytics. Part V consists of case studies of analytical activity within organizations.

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