Camm * Cochran * Fry * Ohlmann * Anderson * Sweeney * Williams

Essentials of Business Analytics 2e

DESCRIPTIVE * PREDICTIVE * PRESCRIPTIVE

Essentials of Business Analytics

2e

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Essentials of Business Analytics, Second Edition
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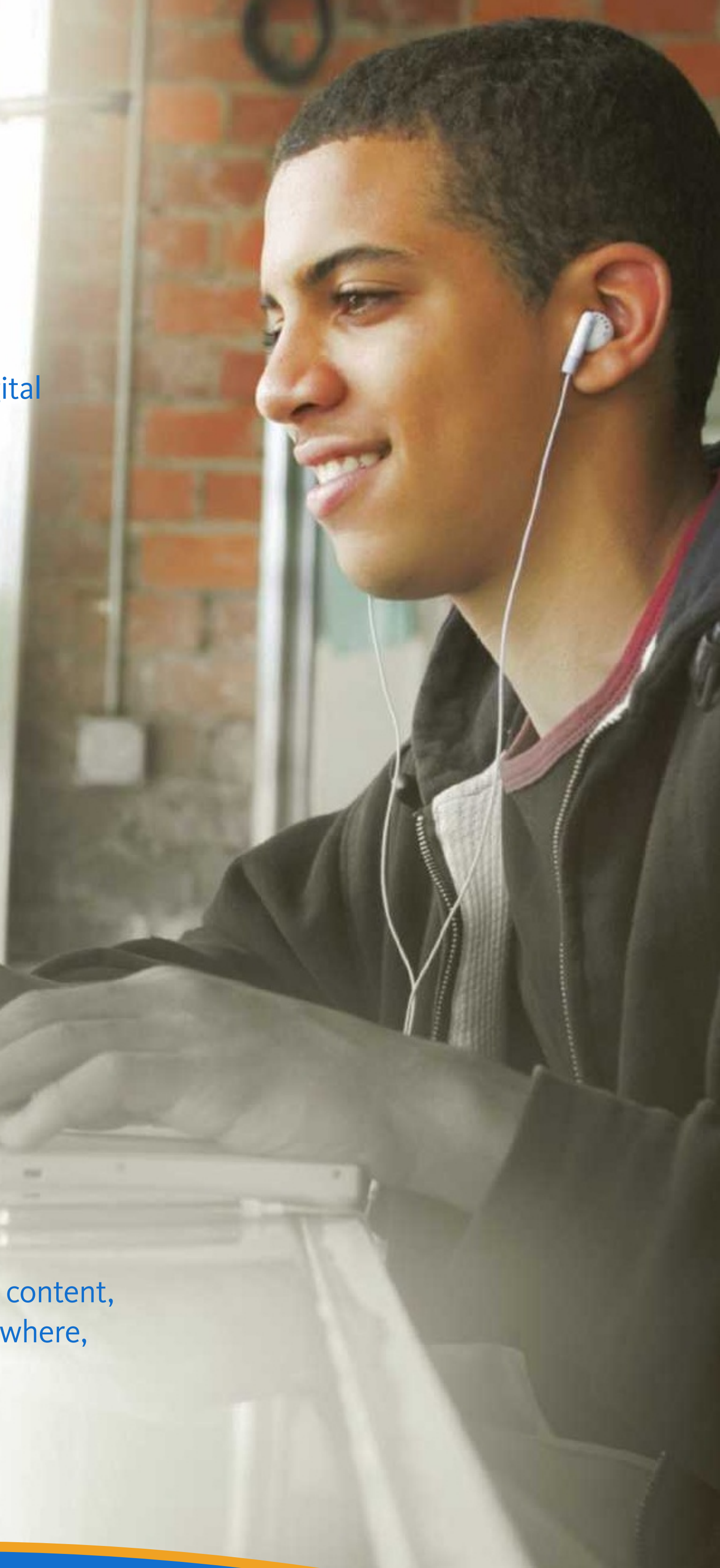

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Jeffrey D. Camm. Jeffrey D. Camm is the Inmar Presidential Chair and Associate Dean of Analytics in the School of Business at Wake Forest University. Born in Cincinnati, Ohio, he holds a B.S. from Xavier University (Ohio) and a Ph.D. from Clemson University. Prior to joining the faculty at Wake Forest, he was on the faculty of the University of Cincinnati. He has also been a visiting scholar at Stanford University and a visiting professor of business administration at the Tuck School of Business at Dartmouth College.

Dr. Camm has published over 30 papers in the general area of optimization applied to problems in operations management and marketing. He has published his research in *Science*, *Management Science*, *Operations Research*, *Interfaces*, and other professional journals. Dr. Camm was named the Dornoff Fellow of Teaching Excellence at the University of Cincinnati and he was the 2006 recipient of the INFORMS Prize for the Teaching of Operations Research Practice. A firm believer in practicing what he preaches, he has served as an operations research consultant to numerous companies and government agencies. From 2005 to 2010 he served as editor-in-chief of *Interfaces.*

James J. Cochran. James J. Cochran is Professor of Applied Statistics and the Rogers-Spivey Faculty Fellow at The University of Alabama. Born in Dayton, Ohio, he earned his B.S., M.S., and M.B.A. degrees from Wright State University and a Ph.D. from the University of Cincinnati. He has been at The University of Alabama since 2014 and has been a visiting scholar at Stanford University, Universidad de Talca, the University of South Africa, and Pole Universitaire Leonard de Vinci.

Professor Cochran has published over three dozen papers in the development and application of operations research and statistical methods. He has published his research in *Management Science, The American Statistician, Communications in Statistics—Theory and Methods, Annals of Operations Research, European Journal of Operational Research, Journal of Combinatorial Optimization. Interfaces, Statistics and Probability Letters*, and other professional journals. He was the 2008 recipient of the INFORMS Prize for the Teaching of Operations Research Practice and the 2010 recipient of the Mu Sigma Rho Statistical Education Award. Professor Cochran was elected to the International Statistics Institute in 2005 and named a Fellow of the American Statistical Association in 2011. He also received the Founders Award in 2014 and the Karl E. Peace Award in 2015 from the American Statistical Association. A strong advocate for effective operations research and statistics education as a means of improving the quality of applications to real problems, Professor Cochran has organized and chaired teaching effectiveness workshops in Montevideo, Uruguay; Cape Town, South Africa; Cartagena, Colombia; Jaipur, India; Buenos Aires, Argentina; and Nairobi, Kenya. He has served as an operations research consultant to numerous companies and not-for profit organizations. He served as editor-in-chief of *INFORMS Transactions on Education* from 2006–2012 and is on the editorial board of *Interfaces, International Transactions in Operational Research*, and *Significance*.

Michael J. Fry. Michael J. Fry is Professor and Head of the Department of Operations, Business Analytics, and Information Systems in the Carl H. Lindner College of Business at the University of Cincinnati. Born in Killeen, Texas, he earned a B.S. from Texas A&M University, and M.S.E. and Ph.D. degrees from the University of Michigan. He has been at the University of Cincinnati since 2002, where he has been named a Lindner Research Fellow and has served as Assistant Director and Interim Director of the Center for Business Analytics. He has also been a visiting professor at the Samuel Curtis Johnson Graduate School of Management at Cornell University and the Sauder School of Business at the University of British Columbia.

Professor Fry has published over twenty research papers in journals such as *Operations Research, M&SOM, Transportation Science, Naval Research Logistics, IIE Transactions,* and *Interfaces*. His research interests are in applying quantitative management methods to the areas of supply chain analytics, sports analytics, and public-policy operations. He has worked with many different organizations for his research, including Dell, Inc., Copeland Corporation, Starbucks Coffee Company, Great American Insurance Group, the Cincinnati Fire Department, the State of Ohio Election Commission, the Cincinnati Bengals, and the Cincinnati Zoo. In 2008, he was named a finalist for the Daniel H. Wagner Prize for Excellence in Operations Research Practice, and he has been recognized for both his research and teaching excellence at the University of Cincinnati.

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Professor Ohlmann's research on the modeling and solution of decision-making problems has produced over a dozen research papers in journals such as *Operations Research, Mathematics of Operations Research, INFORMS Journal on Computing, Transportation Science,* the *European Journal of Operational Research,* and *Interfaces*. He has collaborated with companies such as Transfreight, LeanCor, Cargill, the Hamilton County Board of Elections, and three National Football League franchises. Due to the relevance of his work to industry, he was bestowed the George B. Dantzig Dissertation Award and was recognized as a finalist for the Daniel H. Wagner Prize for Excellence in Operations Research Practice.

David R. Anderson. David R. Anderson is Professor Emeritus of Quantitative Analysis in the Carl H. Lindner College of Business at the University of Cincinnati. Born in Grand Forks, North Dakota, he earned his B.S., M.S., and Ph.D. degrees from Purdue University. Professor Anderson has served as Head of the Department of Quantitative Analysis and Operations Management and as Associate Dean of the College of Business Administration. In addition, he was the coordinator of the College's first Executive Program.

At the University of Cincinnati, Professor Anderson has taught introductory statistics for business students as well as graduate-level courses in regression analysis, multivariate analysis, and management science. He has also taught statistical courses at the Department of Labor in Washington, D.C. He has been honored with nominations and awards for excellence in teaching and excellence in service to student organizations.

Professor Anderson has coauthored 10 textbooks in the areas of statistics, management science, linear programming, and production and operations management. He is an active consultant in the field of sampling and statistical methods.

Dennis J. Sweeney. Dennis J. Sweeney is Professor Emeritus of Quantitative Analysis and Founder of the Center for Productivity Improvement at the University of Cincinnati. Born in Des Moines, Iowa, he earned a B.S.B.A. degree from Drake University and his M.B.A. and D.B.A. degrees from Indiana University, where he was an NDEA Fellow. During 1978–1979, Professor Sweeney worked in the management science group at Procter & Gamble; during 1981–1982, he was a visiting professor at Duke University. Professor Sweeney served as Head of the Department of Quantitative Analysis and as Associate Dean of the College of Business Administration at the University of Cincinnati.

Professor Sweeney has published more than 30 articles and monographs in the areas of management science and statistics. The National Science Foundation, IBM, Procter & Gamble, Federated Department Stores, Kroger, and Cincinnati Gas & Electric have funded his research, which has been published in *Management Science, Operations Research, Mathematical Programming, Decision Sciences,* and other journals.

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Thomas A. Williams. Thomas A. Williams is Professor Emeritus of Management Science in the College of Business at Rochester Institute of Technology. Born in Elmira, New York, he earned his B.S. degree at Clarkson University. He did his graduate work at Rensselaer Polytechnic Institute, where he received his M.S. and Ph.D. degrees.

Before joining the College of Business at RIT, Professor Williams served for seven years as a faculty member in the College of Business Administration at the University of Cincinnati, where he developed the undergraduate program in Information Systems and then served as its coordinator. At RIT he was the first chairman of the Decision Sciences Department. He teaches courses in management science and statistics, as well as graduate courses in regression and decision analysis.

Professor Williams is the coauthor of 11 textbooks in the areas of management science, statistics, production and operations management, and mathematics. He has been a consultant for numerous *Fortune* 500 companies and has worked on projects ranging from the use of data analysis to the development of large-scale regression models.

Preface

Essentials of Business Analytics 2E is designed to introduce the concept of business analytics to undergraduate and graduate students. This textbook contains one of the first collections of materials that are essential to the growing field of business analytics. In Chapter 1 we present an overview of business analytics and our approach to the material in this textbook. In simple terms, business analytics helps business professionals make better decisions based on data. We discuss models for summarizing, visualizing, and understanding useful information from historical data in Chapters 2 through 6. Chapters 7 through 9 introduce methods for both gaining insights from historical data as well as predicting possible future outcomes. Chapter 10 covers the use of spreadsheets for examining data and building decision models. In Chapters 11 through 12 we discuss optimization models to help decision makers choose the best decision based on the available data. Chapter 13 presents material that some may consider more advanced forms of optimization (nonlinear optimization models), although these models are extremely useful and widely applicable to many business situations. In any case, some instructors may choose to omit covering Chapter 13. In Chapter 14 we introduce the concept of simulation models for understanding the effect of uncertainty on decisions. Chapter 15 is an overview of decision analysis approaches for incorporating a decision maker's views about risk into decision making. In Appendix A we present optional material for students who need to learn the basics of using Microsoft Excel. The use of databases and manipulating data in Microsoft Access is discussed in Appendix B.

This textbook can be used by students who have previously taken a course on basic statistical methods as well as students who have not had a prior course in statistics. The expanded material in the second edition of Essentials of Business Analytics also makes it amenable to a two-course sequence in business statistics and analytics. All statistical concepts contained in this textbook are presented from a business analytics perspective using practical business examples. Chapters 2, 5, 6 and 7 provide an introduction to basic statistical concepts that form the foundation for more advanced analytics methods. Chapters 3, 4 and 9 cover additional topics of data visualization and data mining that are not traditionally part of most introductory business statistics courses, but they are exceedingly important and commonly used in current business environments. Chapter 10 and Appendix A provide the foundational knowledge students need to use Microsoft Excel for analytics applications. Chapters 11 through 15 build upon this spreadsheet knowledge to present additional topics that are used by many organizations that are leaders in the use of prescriptive analytics to improve decision making.

Updates in the Second Edition

The second edition of *Essentials of Business Analytics* is a major revision of the first edition. We have added several new chapters, expanded the coverage of existing chapters, and updated all chapters based on changes in the software used with this textbook. Stylistically, the 2nd edition of *Essentials of Business Analytics* also has an entirely new look. We have added full-color figures throughout the textbook that make many chapters much more meaningful and easier to read.

- **New Chapters on Probability and Statistical Inference.** Chapters 5 and 6 are new to this edition. Chapter 5 covers an introduction to probability for those students who are not familiar with basic probability concepts such as random variables, conditional probability, Bayes' theorem, and probability distributions. Chapter 6 presents statistical inference topics such as sampling, sampling distributions, interval estimation, and hypothesis testing. These two chapters extend the basic statistical coverage of *Essentials of Business Analytics* (in conjunction with Chapter 2 on Descriptive Statistics and Chapter 7 on Linear Regression) so that the textbook includes a full coverage of introductory business statistics for students who are unfamiliar with these concepts.

- **Expanded Data Mining Coverage.** The Data Mining chapter from the first edition has been broken into two chapters: Chapter 4 on Descriptive Data Mining and Chapter 9 on Predictive Data Mining. This allows us to cover additional material related to these concepts and to also clearly delineate the different forms of data mining based on their intended result. Chapter 4 on Descriptive Data Mining covers unsupervised learning methods such as clustering and association rules where the user is interested in identifying relationships among observations rather than predicting specific outcome variables. Chapter 4 also covers very important topics related to data preparation including missing data, outliers, and variable representation. Chapter 9 on Predictive Data Mining introduces supervised learning methods that are used to predict an outcome based on a set of input variables. The methods covered in Chapter 9 include logistic regression, *k*-nearest neighbors clustering, and classification and regression trees. Additional data preparation methods such as data sampling and data portioning are also covered in this chapter.
- **Revision of Linear Regression Chapter.** Based on user feedback from the first edition, Chapter 7's coverage of linear regression has been substantially revised to streamline the exposition with a focus on intuitive understanding without sacrificing technical accuracy. The appendix of this chapter has been expanded to demonstrate the construction of prediction intervals using the Analytic Solver Platform software.
- **New Appendix to Chapter 8.** Chapter 8 on Time Series Analysis and Forecasting now includes an appendix on Excel 2016's new Forecast Sheet tool for implementing Holt-Winters additive seasonal smoothing model.
- **Revision of Simulation Chapter.** As with all other chapters, the coverage of Analytics Solver Platform has been moved to the appendix. All material in the body of the chapter uses only native Excel to implement Monte Carlo simulations.
- **Coverage of Analytic Solver Platform (ASP) Moved to Chapter Appendices.** All coverage of the Excel add-in, Analytics Solver Platform, has been moved to the chapter appendices. This means that instructors can now cover all the material in the bodies of the chapters using only native Excel functionality. ASP is used most heavily in the data mining and simulation chapters, so the result of this change is that the chapter appendices are quite long for Chapters 4, 9, and 14. However, this change makes it easier for an instructor to tailor a course's coverage of data mining concepts and the execution of these concepts.
- **Updates to ASP.** All examples, problems, and solutions have been updated in response to changes in the ASP software. Frontline Systems, the developer of ASP, implemented a major rewrite of the code base that powers ASP shortly after the release of the first edition of *Essentials of Business Analytics*. This new code base is much faster and more stable than the previous releases of ASP, but it also completely changed the output given by ASP in many cases. All the material related to ASP is updated to correspond to Analytic Solver Platform V2016 (16.0.0).
- **Incorporation of Excel 2016.** Most updates in Excel 2016 are relatively minor as they relate to its use for statistics and analytics. However, Excel 2016 does have new options for creating Charts in Excel and for implementing forecasting methods. Excel 2016 allows for the creation of box plots, tree maps, and several other data visualization tools that could not be created in previous versions of Excel. Excel's new Forecast Sheet tool implements a time series forecasting model known as the Holt-Winters

additive seasonal smoothing model; this is covered in the appendix to Chapter 8. Several other minor updates to the Ribbon and tabs have also been made in Excel 2016. All material in the second edition of this textbook is easily accessible for students using earlier versions of Excel. For Excel tools that are only implementable in Excel 2016, we include these either in a chapter appendix (such as Forecast Sheet in Chapter 8 appendix) or with margin notes explaining how the same action can be executed in Excel 2013.

- **Additional Excel Features Incorporated.** Several other features that were introduced in Excel 2013 have been more fully incorporated in this edition. Chapter 2 introduces the Quick Analysis button in Excel, and Chapter 3 now makes full use of the Chart Buttons in Excel. The Quick Analysis button is a shortcut method for accomplishing many common Excel formatting and other tasks. The Chart Buttons make it much easier to format, edit, and analyze charts in Excel. Chapter 3 also now also includes coverage of the Recommended PivotTables and Recommended Charts tools in Excel.
- **New Style and More Color.** The second edition of *Essentials of Business Analytics* includes full color figures and a new color template throughout the text. This makes much of the material covered, such as Chapter 3 on Data Visualization, much easier for students to interpret and understand.

Continued Features and Pedagogy

The style of this textbook is based on the other classic textbooks written by the Anderson, Sweeney, and Williams (ASW) team. Some of the specific features that we use in this textbook are listed below.

- **Integration of Microsoft Excel:** Excel has been thoroughly integrated throughout this textbook. For many methodologies, we provide instructions for how to perform calculations both by hand and with Excel. In other cases where realistic models are practical only with the use of a spreadsheet, we focus on the use of Excel to describe the methods to be used.
- **Notes and Comments:** At the end of many sections, we provide Notes and Comments to give the student additional insights about the methods presented in that section. These insights include comments on the limitations of the presented methods, recommendations for applications, and other matters. Additionally, margin notes are used throughout the textbook to provide additional insights and tips related to the specific material being discussed.
- **Analytics in Action:** Each chapter contains an Analytics in Action article. These articles present interesting examples of the use of business analytics in practice. The examples are drawn from many different organizations in a variety of areas including healthcare, finance, manufacturing, marketing, and others.
- **DATAfiles and MODELfiles:** All data sets used as examples and in student exercises are also provided online as files available for download by the student. DATAfiles are Excel files that contain data needed for the examples and problems given in the textbook. MODELfiles contain additional modeling features such as extensive use of Excel formulas or the use of Excel Solver or Analytic Solver Platform.
- **Problems and Cases:** With the exception of Chapter 1, each chapter contains an extensive selection of problems to help the student master the material presented in that chapter. The problems vary in difficulty and most relate to specific examples of the use of business analytics in practice. Answers to even-numbered problems are provided in

an online supplement for student access. With the exception of Chapter 1, each chapter also includes an in-depth case study that connects many of the different methods introduced in the chapter. The case studies are designed to be more open-ended than the chapter problems, but enough detail is provided to give the student some direction in solving the cases.

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For Students

Online resources are available to help the student work more efficiently. The resources can be accessed through **www.cengagebrain.com**.

- **Analytic Solver Platform:** Instructions to download an educational version of Frontline Systems' Analytic Solver Platform are included with the purchase of this textbook. These instructions can be found within the inside front cover of this text.

For Instructors

Instructor resources are available to adopters on the Instructor Companion Site, which can be found and accessed at **www.cengage.com**, including:

- **Solutions Manual:** The Solutions Manual, prepared by the authors, includes solutions for all problems in the text. It is available online as well as print.
- **Solutions to Case Problems:** These are also prepared by the authors and contain solutions to all case problems presented in the text.
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Chapter 1

Introduction

CONTENTS

You apply for a loan for the first time. How does the bank assess the riskiness of the loan it might make to you? How does Amazon.com know which books and other products to recommend to you when you log in to their web site? How do airlines determine what price to quote to you when you are shopping for a plane ticket? How can doctors better diagnose and treat you when you are ill or injured?

You may be applying for a loan for the first time, but millions of people around the world have applied for loans before. Many of these loan recipients have paid back their loans in full and on time, but some have not. The bank wants to know whether you are more like those who have paid back their loans or more like those who defaulted. By comparing your credit history, financial situation, and other factors to the vast database of previous loan recipients, the bank can effectively assess how likely you are to default on a loan.

Similarly, Amazon.com has access to data on millions of purchases made by customers on its web site. Amazon.com examines your previous purchases, the products you have viewed, and any product recommendations you have provided. Amazon.com then searches through its huge database for customers who are similar to you in terms of product purchases, recommendations, and interests. Once similar customers have been identified, their purchases form the basis of the recommendations given to you.

Prices for airline tickets are frequently updated. The price quoted to you for a flight between New York and San Francisco today could be very different from the price that will be quoted tomorrow. These changes happen because airlines use a pricing strategy known as revenue management. Revenue management works by examining vast amounts of data on past airline customer purchases and using these data to forecast future purchases. These forecasts are then fed into sophisticated optimization algorithms that determine the optimal price to charge for a particular flight and when to change that price. Revenue management has resulted in substantial increases in airline revenues.

Finally, consider the case of being evaluated by a doctor for a potentially serious medical issue. Hundreds of medical papers may describe research studies done on patients facing similar diagnoses, and thousands of data points exist on their outcomes. However, it is extremely unlikely that your doctor has read every one of these research papers or is aware of all previous patient outcomes. Instead of relying only on her medical training and knowledge gained from her limited set of previous patients, wouldn't it be better for your doctor to have access to the expertise and patient histories of thousands of doctors around the world?

A group of IBM computer scientists initiated a project to develop a new decision technology to help in answering these types of questions. That technology is called Watson, named after the founder of IBM, Thomas J. Watson. The team at IBM focused on one aim: how the vast amounts of data now available on the Internet can be used to make more data-driven, smarter decisions.

Watson became a household name in 2011, when it famously won the television game show, *Jeopardy!* Since that proof of concept in 2011, IBM has reached agreements with the health insurance provider WellPoint (now part of Anthem), the financial services company Citibank, and Memorial Sloan-Kettering Cancer Center to apply Watson to the decision problems that they face.

Watson is a system of computing hardware, high-speed data processing, and analytical algorithms that are combined to make data-based recommendations. As more and more data are collected, Watson has the capability to learn over time. In simple terms, according to IBM, Watson gathers hundreds of thousands of possible solutions from a huge data bank, evaluates them using analytical techniques, and proposes only the best solutions for consideration. Watson provides not just a single solution, but rather a range of good solutions with a confidence level for each.

For example, at a data center in Virginia, to the delight of doctors and patients, Watson is already being used to speed up the approval of medical procedures. Citibank is beginning to explore how to use Watson to better serve its customers, and cancer specialists at more than a dozen hospitals in North America are using Watson to assist with the diagnosis and treatment of patients.[1]

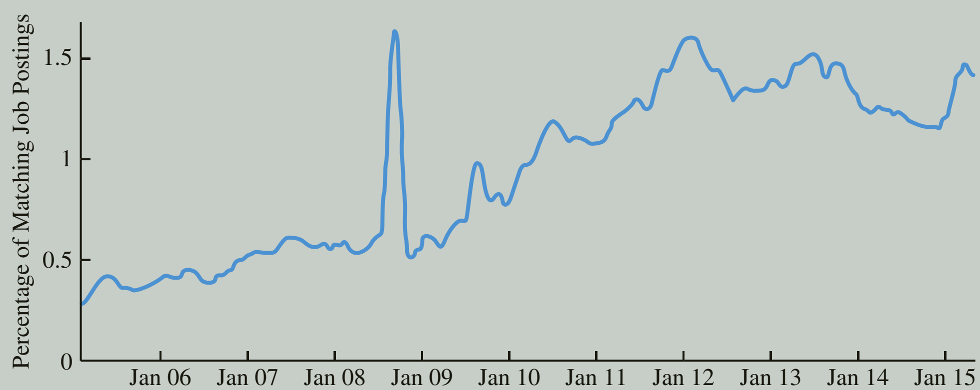
This book is concerned with data-driven decision making and the use of analytical approaches in the decision-making process. Three developments spurred recent explosive growth in the use of analytical methods in business applications. First, technological advances—such as improved point-of-sale scanner technology and the collection of data through e-commerce, Internet social networks, and data generated from personal electronic devices—produce incredible amounts of data for businesses. Naturally, businesses want to use these data to improve the efficiency and profitability of their operations, better understand their customers, price their products more effectively, and gain a competitive advantage. Second, ongoing research has resulted in numerous methodological developments, including advances in computational approaches to effectively handle and explore massive amounts of data, faster algorithms for optimization and simulation, and more effective approaches for visualizing data. Third, these methodological developments were paired with an explosion in computing power and storage capability. Better computing hardware, parallel computing, and, more recently, cloud computing (the remote use of hardware and software over the Internet) have enabled businesses to solve big problems more quickly and more accurately than ever before.

In summary, the availability of massive amounts of data, improvements in analytic methodologies, and substantial increases in computing power have all come together to result in a dramatic upsurge in the use of analytical methods in business and a reliance on the discipline that is the focus of this text: business analytics. Figure 1.1 shows the job trend for analytics from 2006 to 2015. The chart from indeed.com shows the percentage of job ads that contain the word *analytics* and illustrates that demand has grown and continues to be strong for analytical skills.

It is difficult to know for sure the cause of the large spike in analytics job ads in 2008. We do note, however, that the thought-provoking book Competing on Analytics *by Davenport and Harris was published in 2007.*

Business analytics is a crucial area of study for students looking to enhance their employment prospects. It has been predicted that by 2018 there will be a shortage of more than 1.5 million business managers with adequate training in analytics in the United States alone.[2] As stated in the Preface, the purpose of this text is to provide

FIGURE 1.1 Analytics Job Trend According to Indeed.com



[1] "IBM's Watson Is Learning Its Way to Saving Lives," Fastcompany web site, December 8, 2012; "IBM's Watson Targets Cancer and Enlists Prominent Providers in the Fight," ModernHealthcare web site, May 5, 2015.
[2] J. Manyika et al., "Big Data: The Next Frontier for Innovation, Competition and Productivity," McKinsey Global Institute Report, 2011.

students with a sound conceptual understanding of the role that business analytics plays in the decision-making process. To reinforce the applications orientation of the text and to provide a better understanding of the variety of applications in which analytical methods have been used successfully, Analytics in Action articles are presented throughout the book. Each Analytics in Action article summarizes an application of analytical methods in practice.

1.1 Decision Making

It is the responsibility of managers to plan, coordinate, organize, and lead their organizations to better performance. Ultimately, managers' responsibilities require that they make strategic, tactical, or operational decisions. **Strategic decisions** involve higher-level issues concerned with the overall direction of the organization; these decisions define the organization's overall goals and aspirations for the future. Strategic decisions are usually the domain of higher-level executives and have a time horizon of three to five years. **Tactical decisions** concern how the organization should achieve the goals and objectives set by its strategy, and they are usually the responsibility of midlevel management. Tactical decisions usually span a year and thus are revisited annually or even every six months. **Operational decisions** affect how the firm is run from day to day; they are the domain of operations managers, who are the closest to the customer.

Consider the case of the Thoroughbred Running Company (TRC). Historically, TRC had been a catalog-based retail seller of running shoes and apparel. TRC sales revenues grew quickly as it changed its emphasis from catalog-based sales to Internet-based sales. Recently, TRC decided that it should also establish retail stores in the malls and downtown areas of major cities. This strategic decision will take the firm in a new direction that it hopes will complement its Internet-based strategy. TRC middle managers will therefore have to make a variety of tactical decisions in support of this strategic decision, including how many new stores to open this year, where to open these new stores, how many distribution centers will be needed to support the new stores, and where to locate these distribution centers. Operations managers in the stores will need to make day-to-day decisions regarding, for instance, how many pairs of each model and size of shoes to order from the distribution centers and how to schedule their sales personnel's work time.

Regardless of the level within the firm, *decision making* can be defined as the following process:

1. Identify and define the problem.
2. Determine the criteria that will be used to evaluate alternative solutions.
3. Determine the set of alternative solutions.
4. Evaluate the alternatives.
5. Choose an alternative.

If I were given one hour to save the planet, I would spend 59 minutes defining the problem and one minute resolving it.
—Albert Einstein

Step 1 of decision making, identifying and defining the problem, is the most critical. Only if the problem is well-defined, with clear metrics of success or failure (step 2), can a proper approach for solving the problem (steps 3 and 4) be devised. Decision making concludes with the choice of one of the alternatives (step 5).

There are a number of approaches to making decisions: tradition ("We've always done it this way"), intuition ("gut feeling"), and rules of thumb ("As the restaurant owner, I schedule twice the number of waiters and cooks on holidays"). The power of each of these approaches should not be underestimated. Managerial experience and intuition are valuable inputs to making decisions, but what if relevant data were available to help us make more informed decisions? With the vast amounts of data now generated and stored electronically, it is estimated that the amount of data stored by businesses more than doubles every two years. How can managers convert these data into knowledge that they can use to be more efficient and effective in managing their businesses?

1.2 Business Analytics Defined

What makes decision making difficult and challenging? Uncertainty is probably the number one challenge. If we knew how much the demand will be for our product, we could do a much better job of planning and scheduling production. If we knew exactly how long each step in a project will take to be completed, we could better predict the project's cost and completion date. If we knew how stocks will perform, investing would be a lot easier.

Another factor that makes decision making difficult is that we often face such an enormous number of alternatives that we cannot evaluate them all. What is the best combination of stocks to help me meet my financial objectives? What is the best product line for a company that wants to maximize its market share? How should an airline price its tickets so as to maximize revenue?

Some firms and industries use the simpler term, analytics. *Analytics is often thought of as a broader category than business analytics, encompassing the use of analytical techniques in the sciences and engineering as well. In this text, we use* business analytics *and* analytics *synonymously.*

Business analytics is the scientific process of transforming data into insight for making better decisions.[3] Business analytics is used for data-driven or fact-based decision making, which is often seen as more objective than other alternatives for decision making.

As we shall see, the tools of business analytics can aid decision making by creating insights from data, by improving our ability to more accurately forecast for planning, by helping us quantify risk, and by yielding better alternatives through analysis and optimization. A study based on a large sample of firms that was conducted by researchers at MIT's Sloan School of Management and the University of Pennsylvania, concluded that firms guided by data-driven decision making have higher productivity and market value and increased output and profitability.[4]

1.3 A Categorization of Analytical Methods and Models

Business analytics can involve anything from simple reports to the most advanced optimization techniques (methods for finding the best course of action). Analytics is generally thought to comprise three broad categories of techniques: descriptive analytics, predictive analytics, and prescriptive analytics.

Descriptive Analytics

Descriptive analytics encompasses the set of techniques that describes what has happened in the past. Examples are data queries, reports, descriptive statistics, data visualization including data dashboards, some data-mining techniques, and basic what-if spreadsheet models.

Appendix B at the end of this book describes how to use Microsoft Access to conduct data queries.

A **data query** is a request for information with certain characteristics from a database. For example, a query to a manufacturing plant's database might be for all records of shipments to a particular distribution center during the month of March. This query provides descriptive information about these shipments: the number of shipments, how much was included in each shipment, the date each shipment was sent, and so on. A report summarizing relevant historical information for management might be conveyed by the use of descriptive statistics (means, measures of variation, etc.) and data-visualization tools (tables, charts, and maps). Simple descriptive statistics and data-visualization techniques can be used to find patterns or relationships in a large database.

[3] We adopt the definition of analytics developed by the Institute for Operations Research and the Management Sciences (INFORMS).

[4] E. Brynjolfsson, L. M. Hitt, and H. H. Kim, "Strength in Numbers: How Does Data-Driven Decisionmaking Affect Firm Performance?" (April 18, 2013). Available at SSRN, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1819486.

Data dashboards are collections of tables, charts, maps, and summary statistics that are updated as new data become available. Dashboards are used to help management monitor specific aspects of the company's performance related to their decision-making responsibilities. For corporate-level managers, daily data dashboards might summarize sales by region, current inventory levels, and other company-wide metrics; front-line managers may view dashboards that contain metrics related to staffing levels, local inventory levels, and short-term sales forecasts.

Data mining is the use of analytical techniques for better understanding patterns and relationships that exist in large data sets. For example, by analyzing text on social network platforms like Twitter, data-mining techniques (including cluster analysis and sentiment analysis) are used by companies to better understand their customers. By categorizing certain words as positive or negative and keeping track of how often those words appear in tweets, a company like Apple can better understand how its customers are feeling about a product like the Apple Watch.

Predictive Analytics

Predictive analytics consists of techniques that use models constructed from past data to predict the future or ascertain the impact of one variable on another. For example, past data on product sales may be used to construct a mathematical model to predict future sales. This mode can factor in the product's growth trajectory and seasonality based on past patterns. A packaged-food manufacturer may use point-of-sale scanner data from retail outlets to help in estimating the lift in unit sales due to coupons or sales events. Survey data and past purchase behavior may be used to help predict the market share of a new product. All of these are applications of predictive analytics.

Linear regression, time series analysis, some data-mining techniques, and simulation, often referred to as risk analysis, all fall under the banner of predictive analytics. We discuss all of these techniques in greater detail later in this text.

Data mining, previously discussed as a descriptive analytics tool, is also often used in predictive analytics. For example, a large grocery store chain might be interested in developing a targeted marketing campaign that offers a discount coupon on potato chips. By studying historical point-of-sale data, the store may be able to use data mining to predict which customers are the most likely to respond to an offer on discounted chips by purchasing higher-margin items such as beer or soft drinks in addition to the chips, thus increasing the store's overall revenue.

Simulation involves the use of probability and statistics to construct a computer model to study the impact of uncertainty on a decision. For example, banks often use simulation to model investment and default risk in order to stress-test financial models. Simulation is also often used in the pharmaceutical industry to assess the risk of introducing a new drug.

Prescriptive Analytics

Prescriptive analytics differs from descriptive or predictive analytics in that **prescriptive analytics** indicates a best course of action to take; that is, the output of a prescriptive model is a best decision. The airline industry's use of revenue management is an example of a prescriptive analytics. Airlines use past purchasing data as inputs into a model that recommends the best pricing strategy across all flights in order to maximize revenue.

Other examples of prescriptive analytics are portfolio models in finance, supply network design models in operations, and price-markdown models in retailing. Portfolio models use historical investment return data to determine which mix of investments will yield the highest expected return while controlling or limiting exposure to risk. Supply-network design models provide data about plant and distribution center locations that will

TABLE 1.1 Coverage of Business Analytics Topics in This Text

Chapter	Title	Descriptive	Predictive	Prescriptive
1	Introduction	●	●	●
2	Descriptive Statistics	●		
3	Data Visualization	●		
4	Descriptive Data Mining	●		
5	Probability: An Introduction to Modeling Uncertainty	●		
6	Statistical Inference	●		
7	Linear Regression		●	
8	Time Series and Forecasting		●	
9	Predictive Data Mining		●	
10	Spreadsheet Models	●		
11	Linear Optimization Models			●
12	Integer Optimization Models			●
13	Nonlinear Optimization Models			●
14	Simulation		●	●
15	Decision Analysis			●

minimize costs while still meeting customer service requirements. Given historical data, retail price markdown models yield revenue-maximizing discount levels and the timing of discount offers when goods have not sold as planned. All of these models are known as **optimization models**, that is, models that give the best decision subject to the constraints of the situation.

Another type of modeling in the prescriptive analytics category is **simulation optimization**, which combines the use of probability and statistics to model uncertainty with optimization techniques to find good decisions in highly complex and highly uncertain settings. Finally, the techniques of **decision analysis** can be used to develop an optimal strategy when a decision maker is faced with several decision alternatives and an uncertain set of future events. Decision analysis also employs **utility theory**, which assigns values to outcomes based on the decision maker's attitude toward risk, loss, and other factors.

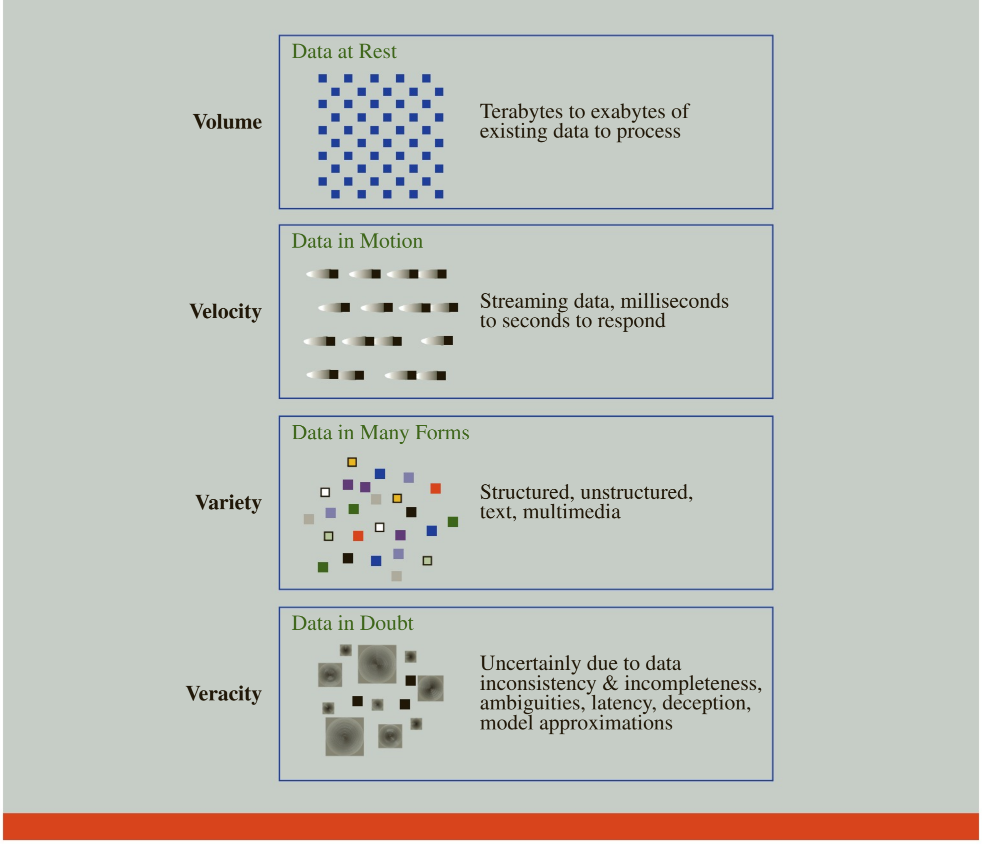
In this text we cover all three areas of business analytics: descriptive, predictive, and prescriptive. Table 1.1 shows how the chapters cover the three categories.

1.4 Big Data

Walmart handles over 1 million purchase transactions per hour. Facebook processes more than 250 million picture uploads per day. Six billion cell-phone owners around the world generate vast amounts of data by calling, texting, tweeting, and browsing the web on a daily basis.[5] As Google CEO Eric Schmidt has noted, the amount of data currently created every 48 hours is equivalent to the entire amount of data created from the dawn of civilization until the year 2003. It is through technology that we have truly been thrust into the data age. Because data can now be collected electronically, the amounts of it available are staggering. The Internet, cell phones, retail checkout scanners, surveillance video, and sensors on everything from aircraft to cars to bridges allow us to collect and store vast amounts of data in real time.

[5]SAS White Paper, "Big Data Meets Big Data Analytics," SAS Institute, 2012.

FIGURE 1.2 The 4 Vs of Big Data



Source: *IBM*

In the midst of all of this data collection, the new term *big data* has been created. There is no universally accepted definition of big data. However, probably the most accepted and most general definition is that **big data** is any set of data that is too large or too complex to be handled by standard data-processing technics and typical desktop software. IBM describes the phenomenon of big data through the four Vs: volume, velocity, variety, and veracity, as shown in Figure 1.2.[6]

Volume

Because data are collected electronically, we are able to collect more of it. To be useful, these data must be stored, and this storage has led to vast quantities of data. Many companies now store in excess of 100 terabytes of data (a terabyte of data is 100,000 gigabytes).

Velocity

Real-time capture and analysis of data present unique challenges both in how data are stored and the speed with which those data can be analyzed for decision making. For example, the New York Stock Exchange collects 1 terabyte of data in a single trading session, and having current data and real-time rules for trades and predictive modeling are important for managing stock portfolios.

[6]IBM web site: http://www.ibmbigdatahub.com/sites/default/files/infographic_file/4-Vs-of-big-data.jpg.

Variety

In addition to the sheer volume and speed with which companies now collect data, more complicated types of data are now available and are proving to be of great value to businesses. Text data are collected by monitoring what is being said about a company's products or services on social media platforms such as Twitter. Audio data are collected from service calls (on a service call, you will often hear "this call may be monitored for quality control"). Video data collected by in-store video cameras are used to analyze shopping behavior. Analyzing information generated by these nontraditional sources is more complicated in part because of the processing required to transform the data into a numerical form that can be analyzed.

Veracity

Veracity has to do with how much uncertainty is in the data. For example, the data could have many missing values, which makes reliable analysis a challenge. Inconsistencies in units of measure and the lack of reliability of responses in terms of bias also increase the complexity of the data.

Businesses have realized that understanding big data can lead to a competitive advantage. Although big data represents opportunities, it also presents challenges in terms of data storage and processing, security and available analytical talent.

The four Vs indicate that big data creates challenges in terms of how these complex data can be captured, stored, and processed; secured; and then analyzed. Traditional databases more or less assume that data fit into nice rows and columns, but that is not always the case with big data. Also, the sheer volume (the first V) often means that it is not possible to store all of the data on a single computer. This has led to new technologies like **Hadoop**—an open-source programming environment that supports big data processing through distributed storage and distributed processing on clusters of computers. Essentially, Hadoop provides a divide-and-conquer approach to handling massive amounts of data, dividing the storage and processing over multiple computers. **MapReduce** is a programming model used within Hadoop that performs the two major steps for which it is named: the map step and the reduce step. The map step divides the data into manageable subsets and distributes it to the computers in the cluster (often termed nodes) for storing and processing. The reduce step collects answers from the nodes and combines them into an answer to the original problem. Without technologies like Hadoop and MapReduce, and relatively inexpensive computer power, processing big data would not be cost-effective; in some cases, processing might not even be possible.

While some sources of big data are publicly available (Twitter, weather data, etc.), much of it is private information. Medical records, bank account information, and credit card transactions, for example, are all highly confidential and must be protected from computer hackers. **Data security**, the protection of stored data from destructive forces or unauthorized users, is of critical importance to companies. For example, credit card transactions are potentially very useful for understanding consumer behavior, but compromise of these data could lead to unauthorized use of the credit card or identity theft. Data security company Datacastle estimated that the average cost of a data breach for a company in 2012 was $7.2 million. Since 2014, companies such as Target, Anthem, JPMorgan Chase, and Home Depot have faced major data breaches costing millions of dollars.

The complexities of the 4 Vs have increased the demand for analysts, but a shortage of qualified analysts has made hiring more challenging. More companies are searching for **data scientists**, who know how to effectively process and analyze massive amounts of data