Introduction to Modeling and Decision Analysis

1.0 Introduction

This book is titled *Spreadsheet Modeling and Decision Analysis: A Practical Introduction to Business Analytics*, so let's begin by discussing exactly what this title means. By the very nature of life, all of us must continually make decisions that we hope will solve problems and lead to increased opportunities, for ourselves or the organizations for which we work. But making good decisions is rarely an easy task. The problems faced by decision makers in today's competitive, data-intensive, fast-paced business environment are often extremely complex and can be addressed by numerous possible courses of action. Evaluating these alternatives and choosing the best course of action represents the essence of decision analysis.

Since the inception of the electronic spreadsheet in the early 1980s, millions of business people have discovered that one of the most effective ways to analyze and evaluate decision alternatives involves using a spreadsheet package to build computer models of the business opportunities and decision problems they face. A **computer model** is a set of mathematical relationships and logical assumptions implemented in a computer as a representation of some real-world object, decision problem, or phenomenon. Today, electronic spreadsheets provide the most convenient and useful way for business people to implement and analyze computer models. Indeed, most business people would probably rate the electronic spreadsheet as their most important analytical tool—apart from their brain! Using a **spreadsheet model** (a computer model implemented via a spreadsheet), a business person can analyze decision alternatives before having to choose a specific plan for implementation.

This book introduces you to a variety of techniques from the field of business analytics that can be applied in spreadsheet models to assist in the decision-analysis process. For our purposes, we will define **business analytics** as a field of study that uses data, computers, statistics, and mathematics to solve business problems. It involves using the methods and tools of science to drive business decision making. It is the science of making better decisions. Business analytics is also sometimes referred to as operations research, management science, or decision science. See Figure 1.1 for a summary of how business analytics has been applied successfully in a number of real-world situations.

In the not too distant past, business analytics was a highly specialized field that generally could be practiced only by those who had access to mainframe computers and who possessed an advanced knowledge of mathematics, computer programming languages, and specialized software packages. However, the proliferation of powerful

FIGURE 1.1

Examples of successful business analytics applications

Home Runs in Business Analytics

Over the past decade, thousands of business analytics projects saved or generated millions of dollars for companies across a variety of industries. Each year, the Institute for Operations Research and the Management Sciences (INFORMS) sponsors the Franz Edelman Awards competition to recognize some of the most outstanding business analytics projects during the past year. Here are some of the "home runs" from the 2013 and 2014 Edelman Awards (described in Interfaces, Vol. 44, No. 1, January–February, 2014 and Vol. 45, No. 1, January–February 2015).

- Chevron created an optimization software tool used at all of its refineries. The company uses this tool for operational and strategic planning to do such things as optimize the mix of crude oils and products to produce, determine refinery operations settings, and plan capital expenditures. This sort of modeling activity is an integral part of Chevron's business processes and culture. Annual savings from Chevron's optimization work is estimated at $1 billion.
- In the1980s, Dell became successful by allowing customers to order custom-configured computers. More recently, Dell ventured into the fixed hardware configurations (FHCs) market to address growing competition. Dell's analytics team used a variety of statistical techniques to create a set of FHCs and to improve its website's design. The analytics team also created models that analyze supply and demand variability to identify when different promotions should be used. These efforts generated more than $140 million by reducing required markdowns, increasing online customer conversion rates, improving logistics, and improving customer satisfaction.
- The Kroger Company operates 1,950 in-store pharmacies throughout its grocery chain. Using actual demand data, its analytics team created a simulation-optimization model to determine reorder points and order-up-to levels for items in its pharmacies. This analytics effort reduced annual out of stocks by 1.6 million prescriptions, lowered inventory by more than $120 million, and increased annual revenue by about $80 million.
- The National Broadcast Network Company (NBNC) is a government-owned entity responsible for providing broadband network service throughout Australia. NBNC recently worked with an analytics consulting company to develop a set of mixed-integer programming models that automate and optimize the design of a network providing broadband coverage to approximately eight million locations. Reductions in design time and other savings have an estimated value of about $1.7 billion.
- The Alliance for Paired Donations (APD) seeks to save lives by securing a living donor kidney for every patient who needs a transplant. People needing a kidney transplant often have a relative or friend willing to donate one, but the donor kidney is often incompatible with the intended recipient. Exchanges with other patient-donor pairs can sometimes overcomes these incompatibilities. The APD uses integer programming techniques to determine the best paired-matches for this kidney exchange problem. Since 2006, the APD's efforts have saved more than 220 lives—and those savings are priceless.

PCs and the development of easy-to-use electronic spreadsheets have made the tools of business analytics far more practical and available to a much larger audience. Virtually everyone who uses a spreadsheet today for model building and decision making is a practitioner of business analytics—whether they realize it or not.

1.1 The Modeling Approach to Decision Making

The idea of using models in problem solving and decision analysis is not new, and is certainly not tied to the use of computers. At some point, all of us have used a modeling approach to make a decision. For example, if you have ever moved into a dormitory, apartment, or house, you undoubtedly faced a decision about how to arrange the furniture in your new dwelling. There were probably a number of different arrangements to consider. One arrangement might give you the most open space but require that you build a loft. Another might give you less space but allow you to avoid the hassle and expense of building a loft. To analyze these different arrangements and make a decision, you did not build the loft. You more likely built a **mental model** of the two arrangements, picturing what each looked like in your mind's eye. Thus, a simple mental model is sometimes all that is required to analyze a problem and make a decision.

For more complex decisions, a mental model might be impossible or insufficient and other types of models might be required. For example, a set of drawings or blueprints for a house or building provides a **visual model** of the real-world structure. These drawings help illustrate how the various parts of the structure will fit together when it is completed. A road map is another type of visual model because it assists a driver in analyzing the various routes from one location to another.

You have probably also seen car commercials on television showing automotive engineers using **physical**, or **scale**, **models** to study the aerodynamics of various car designs to find the shape that creates the least wind resistance and maximizes fuel economy. Similarly, aeronautical engineers use scale models of airplanes to study the flight characteristics of various fuselage and wing designs. And civil engineers might use scale models of buildings and bridges to study the strengths of different construction techniques.

Another common type of model is a **mathematical model**, which uses mathematical relationships to describe or represent an object or decision problem. Throughout this book we will study how various mathematical models can be implemented and analyzed on computers using spreadsheet software. But before we move to an in-depth discussion of spreadsheet models, let's look at some of the more general characteristics and benefits of modeling.

1.2 Characteristics and Benefits of Modeling

Although this book focuses on mathematical models implemented in computers via spreadsheets, the examples of nonmathematical models given earlier are worth discussing a bit more because they help illustrate a number of important characteristics and benefits of modeling in general. First, the models mentioned earlier are usually simplified versions of the object or decision problem they represent. To study the aerodynamics of a car design, we do not need to build the entire car complete with engine and stereo. Such components have little or no effect on aerodynamics. So, although a model is often a simplified representation of reality, the model is useful as long as it is valid. A **valid** model is one that accurately represents the relevant characteristics of the object or decision problem being studied.

Second, it is often less expensive to analyze decision problems using a model. This is especially easy to understand with respect to scale models of big-ticket items such as cars and planes. Besides the lower financial cost of building a model, the analysis of a model can help avoid costly mistakes that might result from poor decision making. For example, it is far less costly to discover a flawed wing design using a scale model of an aircraft than after the crash of a fully loaded jet liner.

Frank Brock, former executive vice president of the Brock Candy Company, related the following story about blueprints his company prepared for a new production facility. After months of careful design work, he proudly showed the plans to several of his production workers. When he asked for their comments, one worker responded, "It's a fine looking building Mr. Brock, but that sugar valve looks like it's about twenty feet away from the steam valve." "What's wrong with that?" asked Brock. "Well, nothing," said the worker, "except that I have to have my hands on both valves at the same time!"[1] Needless to say, it was far less expensive to discover and correct this "little" problem using a visual model before pouring the concrete and laying the pipes as originally planned.

Third, models often deliver needed information on a more timely basis. Again, it is relatively easy to see that scale models of cars or airplanes can be created and analyzed more quickly than their real-world counterparts. Timeliness is also an issue when vital data will not become available until some later point in time. In these cases, we might create a model to help predict the missing data to assist in current decision making.

Fourth, models are frequently helpful in examining things that would be impossible to do in reality. For example, human models (crash dummies) are used in crash tests to see what might happen to an actual person if a car hits a brick wall at a high speed. Likewise, models of DNA can be used to visualize how molecules fit together. Both of these are difficult, if not impossible, to do without the use of models.

Finally, and probably most importantly, models allow us to gain insight and understanding about the object or decision problem under investigation. The ultimate purpose of using models is to improve decision making. As you will see, the process of building a model can shed important light and understanding on a problem. In some cases, a decision might be made while building the model, as a previously misunderstood element of the problem is discovered or eliminated. In other cases, a careful analysis of a completed model might be required to "get a handle" on a problem and gain the insights needed to make a decision. In any event, it is the insight gained from the modeling process that ultimately leads to better decision making.

1.3 Mathematical Models

As mentioned earlier, the modeling techniques in this book differ quite a bit from scale models of cars and planes or visual models of production plants. The models we will build use mathematics to describe a decision problem. We use the term "mathematics" in its broadest sense, encompassing not only the most familiar elements of math, such as algebra, but also the related topic of logic.

Now, let's consider a simple example of a mathematical model:

$$\text{PROFIT} = \text{REVENUE} - \text{EXPENSES} \tag{1.1}$$

[1] Colson, Charles and Jack Eckerd. *Why America Doesn't Work* (Denver, Colorado: Word Publishing, 1991), 146–147.

Equation 1.1 describes a simple relationship between revenue, expenses, and profit. It is a mathematical relationship that describes the operation of determining profit—or a mathematical model of profit. Of course, not all models are this simple, but taken piece by piece, the models we will discuss are not much more complex than this one.

Frequently, mathematical models describe functional relationships. For example, the mathematical model in equation 1.1 describes a functional relationship between revenue, expenses, and profit. Using the symbols of mathematics, this functional relationship is represented as:

$$\text{PROFIT} = f(\text{REVENUE, EXPENSES}) \qquad \textbf{1.2}$$

In words, the previous expression means "profit is a function of revenue and expenses." We could also say that profit *depends* on (or is *dependent* on) revenue and expenses. Thus, the term PROFIT in equation 1.2 represents a **dependent** variable, whereas REVENUE and EXPENSES are **independent** variables. Frequently, compact symbols (such as A, B, and C) are used to represent variables in an equation such as 1.2. For instance, if we let Y, X_1, and X_2 represent PROFIT, REVENUE, and EXPENSES, respectively, we could rewrite equation 1.2 as follows:

$$Y = f(X_1, X_2) \qquad \textbf{1.3}$$

The notation $f(\cdot)$ represents the function that defines the relationship between the dependent variable Y and the independent variables X_1 and X_2. In the case of determining PROFIT from REVENUE and EXPENSES, the mathematical form of the function $f(\cdot)$ is quite simple because we know that $f(X_1, X_2) = X_1 - X_2$. However, in many other situations we will model, the form of $f(\cdot)$ is quite complex and might involve many independent variables. But regardless of the complexity of $f(\cdot)$ or the number of independent variables involved, many of the decision problems encountered in business can be represented by models that assume the general form,

$$Y = f(X_1, X_2, \ldots, X_k) \qquad \textbf{1.4}$$

In equation 1.4, the dependent variable Y represents some bottom-line performance measure of the problem we are modeling. The terms $X_1, X_2, \ldots, X_k$ represent the different independent variables that play some role or have some impact in determining the value of Y. Again, $f(\cdot)$ is the function (possibly quite complex) that specifies or describes the relationship between the dependent and independent variables.

The relationship expressed in equation 1.4 is very similar to what occurs in most spreadsheet models. Consider a simple spreadsheet model to calculate the monthly payment for a car loan, as shown in Figure 1.2.

The spreadsheet in Figure 1.2 contains a variety of **input** cells (e.g., purchase price, down payment, trade-in, term of loan, annual interest rate) that correspond conceptually to the independent variables $X_1, X_2, \ldots, X_k$ in equation 1.4. Similarly, a variety of mathematical operations are performed using these input cells in a manner analogous to the function $f(\cdot)$ in equation 1.4. The results of these mathematical operations determine the value of some **output** cell in the spreadsheet (e.g., monthly payment) that corresponds to the dependent variable Y in equation 1.4. Thus, there is a direct correspondence between equation 1.4 and the spreadsheet in Figure 1.2. This type of correspondence exists for most of the spreadsheet models in this book.

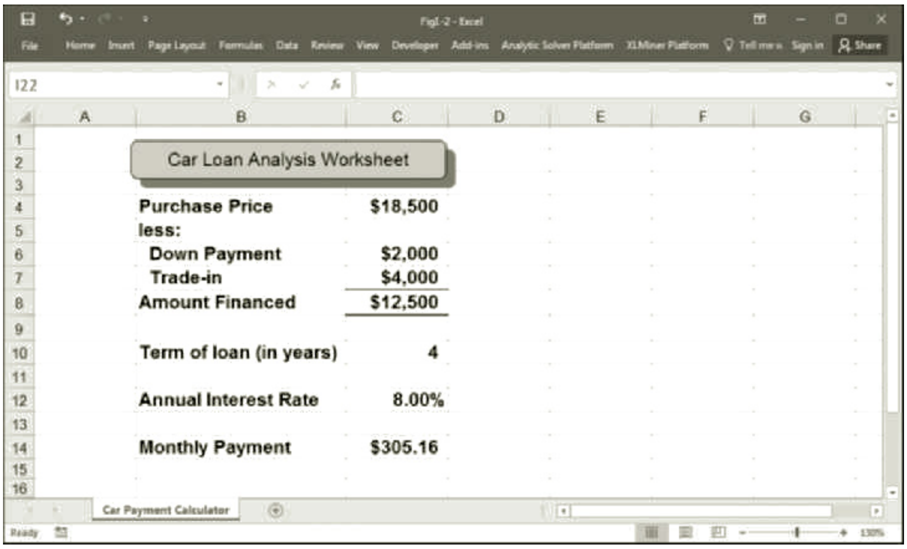

FIGURE 1.2

Example of a simple spreadsheet model

1.4 Categories of Mathematical Models

Not only does equation 1.4 describe the major elements of mathematical or spreadsheet models, but it also provides a convenient means for comparing and contrasting the three categories of modeling techniques presented in this book—Prescriptive Models, Predictive Models, and Descriptive Models. Figure 1.3 summarizes the characteristics and some of the techniques associated with each of these categories.

In some situations, a manager might face a decision problem involving a very precise, well-defined functional relationship $f(\cdot)$ between the independent variables $X_1, X_2, \ldots, X_k$ and the dependent variable Y. If the values for the independent variables are under the decision maker's control, the decision problem in these types of situations boils down

FIGURE 1.3

Categories and characteristics of business analytics modeling techniques

	Model Characteristics:		
Category	**Form of $f(\cdot)$**	**Values of Independent Variables**	**Business Analytics Techniques**
Prescriptive Models	known, well-defined	known or under decision maker's control	Linear Programming, Networks, Integer Programming, CPM, Goal Programming, EOQ, Nonlinear Programming
Predictive Models	unknown, ill-defined	known or under decision maker's control	Regression Analysis, Time Series Analysis, Discriminant Analysis, Neural Networks, Logistic Regression, Affinity Analysis, Cluster Analysis
Descriptive Models	known, well-defined	unknown or uncertain	Simulation, Queuing, PERT, Inventory Models

to determining the values of the independent variables $X_1, X_2, \ldots, X_k$ that produce the best possible value for the dependent variable Y. These types of models are called **prescriptive models** because their solutions tell the decision maker what actions to take. For example, you might be interested in determining how a given sum of money should be allocated to different investments (represented by the independent variables) to maximize the return on a portfolio without exceeding a certain level of risk.

A second category of decision problems is one in which the objective is to predict or estimate what value the dependent variable Y will take on when the independent variables $X_1, X_2, \ldots, X_k$ take on specific values. If the function $f(\cdot)$ relating the dependent and independent variables is known, this is a very simple task—simply enter the specified values for $X_1, X_2, \ldots, X_k$ into the function $f(\cdot)$ and compute Y. In some cases, however, the functional form of $f(\cdot)$ might be unknown and must be estimated in order for the decision maker to make predictions about the dependent variable Y. These types of models are called **predictive models**. For example, a real estate appraiser might know that the value of a commercial property (Y) is influenced by its total square footage (X_1) and age (X_2), among other things. However, the functional relationship $f(\cdot)$ that relates these variables to one another might be unknown. By analyzing the relationship between the selling price, total square footage, and age of other commercial properties, the appraiser might be able to identify a function $f(\cdot)$ that relates these variables in a reasonably accurate manner.

The third category of models you are likely to encounter in the business world is called **descriptive models**. In these situations, a manager might face a decision problem that has a very precise, well-defined functional relationship $f(\cdot)$ between the independent variables $X_1, X_2, \ldots, X_k$ and the dependent variable Y. However, there might be great uncertainty as to the exact values that will be assumed by one or more of the independent variables $X_1, X_2, \ldots, X_k$. In these types of problems, the objective is to describe the outcome or behavior of a given operation or system. For example, suppose a company is building a new manufacturing facility and has several choices about the type of machines to put in the new plant, as well as various options for arranging the machines. Management might be interested in studying how the various plant configurations would affect on-time shipments of orders (Y), given the uncertain number of orders that might be received (X_1) and the uncertain due dates (X_2) that might be required by these orders.

1.5 Business Analytics and the Problem-Solving Process

Business analytics focuses on identifying and leveraging business opportunities. But business ***opportunities*** can often be viewed or formulated as decision ***problems*** that need to be solved. As a result, the words "opportunity" and "problem" are used somewhat synonymously throughout this book. Indeed, some use the phrase "probortunity" to denote that every problem is also an opportunity.

Throughout our discussion, we have said that the ultimate goal in building models is to assist managers in making decisions that solve problems. The modeling techniques we will study represent a small but important part of the total problem-solving process. The "problem-solving process" discussed here is usually focused on leveraging a business opportunity of one sort or another. To become an effective modeler, it is important to understand how modeling fits into the entire problem-solving process. Because a model can be used to represent a decision problem or phenomenon, we

FIGURE 1.4

A visual model of the problem-solving process

might be able to create a visual model of the phenomenon that occurs when people solve problems—what we call the problem-solving process. Although a variety of models could be equally valid, the one in Figure 1.4 summarizes the key elements of the problem-solving process and is sufficient for our purposes.

The first step of the problem-solving process, identifying the problem (or 'probortunity'), is also the most important. If we do not identify the correct decision problem associated with the business opportunity at hand, all the work that follows will amount to nothing more than wasted effort, time, and money. Unfortunately, identifying the problem to solve is often not as easy as it seems. We know that a problem exists when there is a gap or disparity between the present situation and some desired state of affairs. However, we usually are not faced with a neat, well-defined problem. Instead, we often find ourselves facing a "mess"![2] Identifying the real problem involves gathering a lot of information and talking with many people to increase our understanding of the mess. We must then sift through all this information and try to identify the root problem or problems causing the mess. Thus, identifying the real problem (and not just the symptoms of the problem) requires insight, some imagination, time, and a good bit of detective work.

The end result of the problem-identification step is a well-defined statement of the problem. Simply defining a problem well will often make it much easier to solve. There is much truth in the saying, "A problem clearly stated is a problem half solved." Having identified the problem, we turn our attention to creating or formulating a model of the problem. Depending on the nature of the problem, we might use a mental model, a visual model, a scale model, or a mathematical model. Although this book focuses on mathematical models, this does not mean that mathematical models are always applicable or best. In most situations, the best model is the simplest model that accurately reflects the relevant characteristic or essence of the problem being studied.

We will discuss several different business analytics techniques in this book. It is important that you not develop too strong a preference for any one technique. Some people want to formulate every problem they face as something that can be solved by their favorite modeling technique. This simply will not work.

As indicated earlier in Figure 1.3, there are fundamental differences in the types of problems a manager might face. Sometimes, the values of the independent variables affecting a problem are under the manager's control; sometimes they are not. Sometimes, the form of the functional relationship $f(\cdot)$ relating the dependent and independent variables is well-defined, and sometimes it is not. These fundamental characteristics of the problem should guide your selection of an appropriate business analytics modeling technique. Your goal at the model-formulation stage is to select a modeling technique that fits your problem, rather than trying to fit your problem into the required format of a preselected modeling technique.

After you select an appropriate representation or formulation of your problem, the next step is to implement this formulation as a spreadsheet model. We will not dwell on the implementation process now because that is the focus of the remainder of this

[2] This characterization is borrowed from James R. Evans, *Creative Thinking in the Decision and Management Sciences* (Cincinnati, Ohio: South-Western Publishing, 1991), 89–115.

book. After you verify that your spreadsheet model has been implemented accurately, the next step in the problem-solving process is to use the model to analyze the problem it represents. The main focus of this step is to generate and evaluate alternatives that might lead to a solution of the problem. This often involves playing out a number of scenarios or asking several "What if?" questions. Spreadsheets are particularly helpful in analyzing mathematical models in this manner. In a well-designed spreadsheet model, it should be fairly simple to change some of the assumptions in the model to see what might happen in different situations. As we proceed, we will highlight some techniques for designing spreadsheet models that facilitate this type of "What if" analysis. "What if" analysis is also very appropriate and useful when working with nonmathematical models.

The end result of analyzing a model does not always provide a solution to the actual problem being studied. As we analyze a model by asking various "What if?" questions, it is important to test the feasibility and quality of each potential solution. The blueprints Frank Brock showed to his production employees represented the end result of his analysis of the problem he faced. He wisely tested the feasibility and quality of this alternative before implementing it, and discovered an important flaw in his plans. Thus, the testing process can give important new insights into the nature of a problem. The testing process is also important because it provides the opportunity to double check the validity of the model. At times, we might discover an alternative that appears to be too good to be true. This could lead us to find that some important assumption has been left out of the model. Testing the results of the model against known results (and simple common sense) helps ensure the structural integrity and validity of the model. After analyzing the model, we might discover that we need to go back and modify it.

The last step of the problem-solving process, implementation, is often the most difficult. Implementation begins by deriving managerial insights from our modeling efforts, framed in the context of the real-world problem we are solving, and communicating those insights to influence actions that affect the business situation. This requires crafting a message that is understood by various stakeholders in an organization and persuading them to take a particular course of action. (See Grossman *et al.*, 2008 for numerous helpful suggestions on this process.) It has been said that managers would rather live with problems they cannot solve than accept solutions they cannot understand. Making solutions understandable and acceptable is the heart of the implementation process.

By their very nature, solutions to problems involve people and change. For better or for worse, most people resist change. However, there are ways to minimize the seemingly inevitable resistance to change. For example, it is wise, if possible, to involve anyone who will be affected by the decision in all steps of the problem-solving process. This not only helps develop a sense of ownership and understanding of the ultimate solution, but it also can be the source of important information throughout the problem-solving process. As the Brock Candy story illustrates, even if it is impossible to include those affected by the solution in all steps, their input should be solicited and considered before a solution is accepted for implementation. Resistance to change and new systems can also be eased by creating flexible, user-friendly interfaces for the mathematical models that are often developed in the problem-solving process.

Throughout this book, we focus mostly on the model formulation, implementation, analysis, and testing steps of the problem-solving process, summarized previously in Figure 1.4. Again, this does not imply that these steps are more important than the others. If we do not identify the correct problem, the best we can hope for from our modeling effort is "the right answer to the wrong question," which does not solve the real problem. Similarly, even if we do identify the problem correctly and design a model that leads to a perfect solution, if we cannot implement the solution, then we still have not solved the problem. Developing the interpersonal and investigative skills required to work with people in defining the problem and implementing the solution is as important as the mathematical modeling skills you will develop by working through this book.

1.6 Anchoring and Framing Effects

At this point, some of you are probably thinking it is better to rely on subjective judgment and intuition rather than models when making decisions. Indeed, most nontrivial decision problems involve some issues that are difficult or impossible to structure and analyze as a mathematical model. These unstructurable aspects of a decision problem may require the use of judgment and intuition. However, it is important to realize that human cognition is often flawed and can lead to incorrect judgments and irrational decisions. Errors in human judgment often arise because of what psychologists term **anchoring** and **framing** effects associated with decision problems.

Anchoring effects arise when a seemingly trivial factor serves as a starting point (or anchor) for estimations in a decision-making problem. Decision makers adjust their estimates from this anchor but nevertheless remain too close to the anchor and usually under-adjust. In a classic psychological study on this issue, one group of subjects were asked to individually estimate the value of $1 \times 2 \times 3 \times 4 \times 5 \times 6 \times 7 \times 8$ (without using a calculator). Another group of subjects were each asked to estimate the value of $8 \times 7 \times 6 \times 5 \times 4 \times 3 \times 2 \times 1$. The researchers hypothesized that the first number presented (or perhaps the product of the first three or four numbers) would serve as a mental anchor. The results supported the hypothesis. The median estimate of subjects shown the numbers in ascending sequence ($1 \times 2 \times 3$ . . .) was 512, whereas the median estimate of subjects shown the sequence in descending order ($8 \times 7 \times 6$ . . .) was 2,250. Of course, the order of multiplication for these numbers is irrelevant and the product of both series is the same: 40,320.

~~Framing effects refer to how a decision maker views or perceives the alternatives in a decision problem—often involving a win/loss perspective. The way a problem is framed often influences the choices made by a decision maker and can lead to irrational behavior~~. For example, suppose you have just been given \$1,000 but must choose one of the following alternatives: (A_1) Receive an additional \$500 with certainty, or (B_1) Flip a fair coin and receive an additional \$1,000 if heads occurs or \$0 additional if tails occurs. Here, alternative A_1 is a "sure win" and is the alternative most people prefer. Now suppose you have been given \$2,000 and must choose one of the following alternatives: (A_2) Give back \$500 immediately, or (B_2) Flip a fair coin and give back \$0 if heads occurs or \$1,000 if tails occurs. When the problem is framed this way, alternative A_2 is a "sure loss" and many people who previously preferred alternative A_1 now opt for alternative B_2 (because it holds a chance of avoiding a loss). However, Figure 1.5 shows a single decision tree for these two scenarios making it clear that, in both cases, the "A" alternative guarantees a total payoff of \$1,500, whereas the "B" alternative offers a 50% chance of a \$2,000 total payoff and a 50% chance of a \$1,000 total payoff. (Decision trees will be covered in greater detail in a later chapter.) A purely rational decision maker should focus on the consequences of his or her choices and consistently select the same alternative, regardless of how the problem is framed.

Whether we want to admit it or not, we are all prone to make errors in estimation due to anchoring effects and may exhibit irrationality in decision making due to

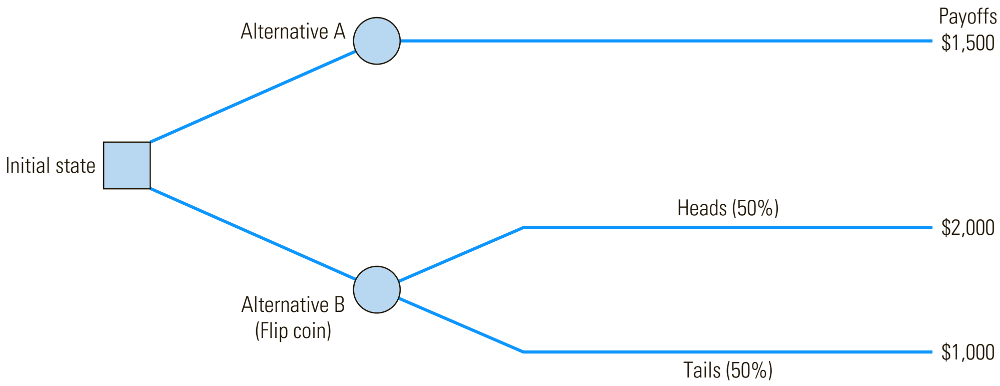

FIGURE 1.5

Decision tree for framing effects

framing effects. As a result, it is best to use computer models to do what they are best at (i.e., modeling structurable portions of a decision problem) and let the human brain do what it is best at (i.e., dealing with the unstructurable portion of a decision problem).

1.7 Good Decisions vs. Good Outcomes

The goal of the modeling approach to problem solving is to help individuals make good decisions. But good decisions do not always result in good outcomes. For example, suppose the weather report on the evening news predicts a warm, dry, sunny day tomorrow. When you get up and look out the window tomorrow morning, suppose there is not a cloud in sight. If you decide to leave your umbrella at home and subsequently get soaked in an unexpected afternoon thundershower, did you make a bad decision? Certainly not. Unforeseeable circumstances beyond your control caused you to experience a bad outcome, but it would be unfair to say that you made a bad decision. A good decision is one that is in harmony with what you know, what you want, what you can do, and to which you are committed. But good decisions sometimes result in bad outcomes. See Figure 1.6 for the story of another good decision having a bad outcome.

Andre-Francois Raffray thought he had a great deal in 1965 when he agreed to pay a 90-year-old woman named Jeanne Calment $500 a month until she died to acquire her grand apartment in Arles, northwest of Marseilles in the south of France—a town Vincent Van Gogh once roamed. Buying apartments "for life" is common in France. The elderly owner gets to enjoy a monthly income from the buyer who gambles on getting a real estate bargain—betting the owner doesn't live too long. Upon the owner's death, the buyer inherits the apartment regardless of how much was paid. But in December of 1995, Raffray died at age 77, having paid more than $180,000 for an apartment he never got to live in.

On the same day, Calment, then the world's oldest living person at 120, dined on foie gras, duck thighs, cheese, and chocolate cake at her nursing home near the sought-after apartment. And she does not need to worry about losing her $500 monthly income. Although the amount Raffray already paid is twice the apartment's current market value, his widow is obligated to keep sending the monthly check to Calment. If Calment also outlives her, then the Raffray children will have to pay. "In life, one sometimes makes bad deals," said Calment of the outcome of Raffray's decision. (Source: The Savannah Morning News, 12/29/95.)

FIGURE 1.6

A good decision with a bad outcome

FIGURE 1.7

Decision quality and outcome quality matrix

		Outcome Quality	
		Good	Bad
Decision Quality	Good	Deserved Success	Bad Luck
	Bad	Dumb Luck	Poetic Justice

Adapted from: J. Russo and P. Shoemaker, *Winning Decisions* (New York, NY: Doubleday, 2002).

The modeling techniques presented in this book can help you make good decisions, but cannot guarantee that good outcomes will always occur as a result of those decisions. Figure 1.7 describes the possible combinations of good and bad decisions and good and bad outcomes. When a good or bad decision is made, luck often plays a role in determining whether a good or bad outcome occurs. However, consistently using a structured, data-driven, and model-based process to make decisions should produce good outcomes (and deserved success) more frequently than making decisions in a more haphazard manner.

1.8 Summary

This book introduces you to a variety of techniques from the field of business analytics that can be applied in spreadsheet models to assist in decision analysis and problem solving. This chapter discussed how spreadsheet models of decision problems can be used to analyze the consequences of possible courses of action before a particular alternative is selected for implementation. It described how models of decision problems differ in a number of important characteristics and how you should select a modeling technique that is most appropriate for the type of problem being faced. It discussed how spreadsheet modeling and analysis fit into the problem-solving process. It then discussed how the psychological phenomena of anchoring and framing can influence human judgment and decision making. Finally, it described the importance of distinguishing between the quality of a decision-making process and the quality of decision outcomes.

1.9 References

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THE WORLD OF BUSINESS ANALYTICS

"Business Analysts Trained in Management Science Can Be a Secret Weapon in a CIO's Quest for Bottom-Line Results."

Efficiency nuts. These are the people you see at cocktail parties explaining how the host could disperse that crowd around the popular shrimp dip if he would divide it into three bowls and place them around the room. As she draws the improved traffic flow on a paper napkin, you notice that her favorite word is "optimize"—a tell-tale sign she has studied the field of "operations research" or "management science" (also known as OR/MS or business analytics).

OR/MS professionals are driven to solve logistics problems. This trait may not make them the most popular people at parties but is exactly what today's information systems (IS) departments need to deliver more business value. Experts say smart IS executives will learn to exploit the talents of these mathematical wizards in their quest to boost a company's bottom line.

According to Ron J. Ponder, chief information officer (CIO) at Sprint Corp. in Kansas City, Mo. and former CIO at Federal Express Corp., "If IS departments had more participation from operations research analysts, they would be building much better, richer IS solutions." As someone who has a Ph.D. in operations research and who built the renowned package-tracking systems at Federal Express, Ponder is a true believer in OR/MS. Ponder and others say analysts trained in OR/MS can turn ordinary information systems into money-saving, decision-support systems and are ideally suited to be members of the business process reengineering team. "I've always had an operations research department reporting to me, and it's been invaluable. Now I'm building one at Sprint," says Ponder.

The Beginnings

OR/MS got its start in World War II, when the military had to make important decisions about allocating scarce resources to various military operations. One of the first business applications for computers in the 1950s was to solve operations research problems for the petroleum industry. A technique called linear programming was used to figure out how to blend gasoline for the right flash point, viscosity, and octane in the most economical way. Since then, OR/MS has spread throughout business and government, from designing efficient drive-thru window operations for Burger King Corp. to creating ultrasophisticated computerized stock trading systems.

A classic OR/MS example is the crew scheduling problem faced by all major airlines. How do you plan the itineraries of 8,000 pilots and 17,000 flight attendants when there is an astronomical number of combinations of planes, crews, and cities? The OR/MS analysts at United Airlines came up with a scheduling system called Paragon that attempts to minimize the amount of paid time that crews spend waiting for flights. Their model factors in constraints such as union rules and Federal Aviation Administration regulations and is projected to save the airline at least $1 million a year.

(Continued)

OR/MS TODAY

Today's OR/MS professionals are involved in a variety of business analytics projects, including the analysis of social media data, inventory assortment planning and management, text mining of online customer comments, computer-integrated manufacturing, cyber-security, healthcare management, and cognitive computing. OR/MS analysts can also model how a business process works now and simulate how it could work more efficiently in the future. Therefore, it makes sense to have an OR/MS analyst on the interdisciplinary team that tackles business process reengineering projects. In essence, OR/MS professionals add more value to businesses by building "tools that really help decision makers analyze complex situations," says Andrew B. Whinston, director of the Center for Information Systems Management at the University of Texas at Austin.

Thomas M. Cook, president of American Airlines Decision Technologies, Inc., says that adding OR/MS skills to anIS team can produce intelligent systems that actually recommend solutions to business problems. One of the big success stories at Cook's operations research shop is a "yield management" system that decides how much to overbook and how to set prices for each seat so that a plane is filled up and profits are maximized. The yield management system deals with more than 250 decision variables and accounts for a significant amount of American Airlines' revenue.

Where to Start

So how can the CIO start down the road toward collaboration with OR/MS analysts? If the company already has a group of OR/MS professionals, the IS department can draw on their expertise as internal consultants. Otherwise, the CIO can simply hire a few OR/MS wizards, throw a problem at them, and see what happens. The payback may come surprisingly fast. As one former OR/MS professional put it: "If I couldn't save my employer the equivalent of my own salary in the first month of the year, then I wouldn't feel like I was doing my job."

Adapted from: Mitch Betts, "Efficiency Einsteins," *ComputerWorld*, March 22, 1993, p. 64.

Questions and Problems

1. What is meant by the term decision analysis?
2. Define the term computer model.
3. What is the difference between a spreadsheet model and a computer model?
4. Define the term business analytics.
5. What is the relationship between business analytics and spreadsheet modeling?
6. What kinds of spreadsheet applications would not be considered business analytics?
7. In what ways do spreadsheet models facilitate the decision-making process?
8. What are the benefits of using a modeling approach to decision making?
9. What is a dependent variable?
10. What is an independent variable?

11. Can a model have more than one dependent variable?
12. Can a decision problem have more than one dependent variable?
13. In what ways are prescriptive models different from descriptive models?
14. In what ways are prescriptive models different from predictive models?
15. In what ways are descriptive models different from predictive models?
16. How would you define the words description, prediction, and prescription? Carefully consider what is unique about the meaning of each word.
17. Identify one or more mental models you have used. Can any of them be expressed mathematically? If so, identify the dependent and independent variables in your model.
18. Consider the spreadsheet model shown in Figure 1.2. Is this model descriptive, predictive, or prescriptive in nature, or does it not fall into any of these categories?
19. Discuss the meaning of the phrase "probortunity."
20. What are the steps in the problem-solving process?
21. Which step in the problem-solving process do you think is most important? Why?
22. Must a model accurately represent every detail of a decision situation to be useful? Why or why not?
23. If you were presented with several different models of a given decision problem, which would you be most inclined to use? Why?
24. Describe an example in which business or political organizations may use anchoring effects to influence decision making.
25. Describe an example in which business or political organizations may use framing effects to influence decision making.
26. Suppose sharks have been spotted along the beach where you are vacationing with a friend. You and your friend have been informed of the shark sightings and are aware of the damage a shark attack can inflict on human flesh. You both decide (individually) to go swimming anyway. You are promptly attacked by a shark while your friend has a nice time body surfing in the waves. Did you make a good or bad decision? Did your friend make a good or bad decision? Explain your answer.
27. Describe an example in which a well-known business, political, or military leader made a good decision that resulted in a bad outcome, or a bad decision that resulted in a good outcome.

Patrick's Paradox

CASE 1.1

Patrick's luck had changed over night – but not his skill at mathematical reasoning. The day after graduating from college he used the $20 that his grandmother had given him as a graduation gift to buy a lottery ticket. He knew his chances of winning the lottery were extremely low and it probably was not a good way to spend this money. But he also remembered from the class he took in business analytics that bad decisions sometimes result in good outcomes. So he said to himself, "What the heck? Maybe this bad decision will be the one with a good outcome." And with that thought, he bought his lottery ticket.

The next day Patrick pulled the crumpled lottery ticket out of the back pocket of his bluejeans and tried to compare his numbers to the winning numbers printed in the paper. When his eyes finally came into focus on the numbers they also just about popped out of his head. He had a winning ticket! In the ensuing days he learned that his share of the jackpot would give him a lump sum payout of about $500,000 after taxes. He knew what he was going to do with part of the money, buy a new car, pay off his college loans, and send his grandmother on an all expenses paid trip to Hawaii. But he also knew that he couldn't continue to hope for good outcomes to arise from more bad decisions. So he decided to take half of his winnings and invest it for his retirement.

A few days later, Patrick was sitting around with two of his fraternity buddies, Josh and Peyton, trying to figure out how much money his new retirement fund might be worth in 30 years. They were all business majors in college and remembered from their finance class that if you invest p dollars for n years at an annual interest rate of i percent then in n years you would have $p(1 + i)^n$ dollars. So they figure that if Patrick invested \$250,000 for 30 years in an investment with a 10% annual return, then in 30 years he would have \$4,362,351 (i.e., $\$250{,}000(1 + 0.10)^{30}$).

But after thinking about it a little more, they all agreed that it would be unlikely for Patrick to find an investment that would produce a return of exactly 10% each and every year for the next 30 years. If any of this money is invested in stocks, then some years the return might be higher than 10% and some years it would probably be lower. So to help account for the potential variability in the investment returns Patrick and his friends came up with a plan; they would assume he could find an investment that would produce an annual return of 17.5% seventy percent of the time and a return (or actually a loss) of −7.5% thirty percent of the time. Such an investment should produce an average annual return of $0.7(17.5\%) + 0.3(-7.5\%) = 10\%$. Josh felt certain that this meant Patrick could still expect his \$250,000 investment to grow to \$4,362,351 in 30 years (because $\$250{,}000(1 + 0.10)^{30} = \$4{,}362{,}351$).

After sitting quietly and thinking about it for a while, Peyton said that he thought Josh was wrong. The way Peyton looked at it, Patrick should see a 17.5% return in 70% of the 30 years (or $0.7(30) = 21$ years) and a −7.5% return in 30% of the 30 years (or $0.3(30) = 9$ years). So, according to Peyton, that would mean Patrick should have $\$250{,}000(1 + 0.175)^{21}(1 - 0.075)^9 = \$3{,}664{,}467$ after 30 years. But that's \$697,884 less than what Josh says Patrick should have.

After listening to Peyton's argument, Josh said he thought Peyton was wrong because his calculation assumes that the "good" return of 17.5% would occur in each of the first 21 years and the "bad" return of −7.5% would occur in each of the last 9 years. But Peyton countered this argument by saying that the order of good and bad returns does not matter. The commutative law of arithmetic says that when you add or multiply numbers, the order doesn't matter (i.e., $X + Y = Y + X$ and $X \times Y = Y \times X$). So Peyton says that because Patrick can expect 21 "good" returns and 9 "bad" returns and it doesn't matter in what order they occur, then the expected outcome of the investment should be \$3,664,467 after 30 years.

Patrick is now really confused. Both of his friends' arguments seem to make perfect sense logically—but they lead to such different answers, and they can't both be right. What really worries Patrick is that he is starting his new job as a business analyst in a couple of weeks. And if he can't reason his way to the right answer in a relatively simple problem like this, what is he going to do when he encounters the more difficult problems awaiting him the business world? Now he really wishes he had paid more attention in his business analytics class.

So what do you think? Who is right, Joshua or Peyton? And more importantly, why?