CHAPTER 2

The Value of Information

Information plays a central role in many of the key concepts in marketing such as market and customer orientation, quality, and satisfaction assessment. Day (1991) and Glazer (1991) describe knowledge and the ability to learn about markets as a key competency and source of competitive advantage. In this chapter, we explore three aspects of information: (1) what it is used for; (2) what influences its use; and (3) how it can be valued.

INTRODUCTION

One reason information is valuable is that, in general, we don’t know as much as we think we do and what we think we know is often wrong. One clear example of not knowing as much as we think we do is overconfidence (cf. Mahajan, 1992). Typically when we forecast, we place too small a range around a forecast. For example, if you ask a number of people for a forecast of, say, sales of a new product (e.g., HDTV) and a range in which they are 90 percent sure the actual result will fall, you will find only something like 10–20 percent of the forecasts will fall in the 90 percent range of an individual. This tendency is actually stronger for experts than for novices. While overconfidence can be reduced by highlighting extreme possible results and encouraging people to think of what could cause a result to be different, its prevalence suggests we may need more information than we think we do. Similarly, in a study by Armstrong (1991), a sample of experts was asked to rate the likelihood that 20 hypotheses about consumer behavior “proved” to be true as in articles in the Journal of Consumer Research. The percent of correct responses was remarkably similar and close to 50 percent (range 51–58%) for three groups: practitioners, academics, and high school students. The conclusion is pretty clear: we don’t do much better than chance in predicting many aspects of behavior based on experience and intuition.

Information needs exist for both new and existing brands. While the impetus for Kodak’s Disc Camera was the peaking of Instamatic sales in 1978, the design was the result of research indicating that “trouble-free” photography in a broader range of situations than was possible with Instamatics had appeal to the market. Design of specific

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features followed extensive customer testing. The introduction of the Disc Camera and subsequent products such as the Falcon, a single-use camera first introduced in Japan in 1994, represent blends of marketing, marketing research, and research and development (which doesn’t always guarantee great success).

Research is often less dramatic but at least as prevalent among existing brands. Consider Gillette and its mature products: razors and razor blades. Their research includes annual national surveys of men and women, an annual interview of an existing panel, a national telephone brand awareness study, numerous consumer use tests, and their own as well as syndicated retail audits. Thus, the collection of information plays a crucial role in many companies.

The basic thrust of this chapter is that the value of information is related to the improvement to which it leads in actual decisions. When considering the value of information, it is important to recognize that many uses of information are only indirectly related to decisions, profit and loss calculations, or both. In addition to aiding decision making, information also is collected for the following reasons:

*Tradition.* As is the case with any organization, patterns of behavior become established. A budget allocated to research is a budget that will be spent. While marketing research typically is a very weak competitor in the bureaucratic battles for funds, it does have a certain permanence: Those involved in information collection and analysis tend to recommend further research.

*To gain agreement.* Often, research is used not to influence the person who orders the research (who has already made a decision) but as a document to gain support for the decision within the organization. Here, research serves both a legitimization and a quality control function.

*To prepare a defense in case of failure.* Research serves as a defense in case a decision goes awry. While there is a fairly low limit to the number of blunders a person can be associated with and still be employed, it is a lot easier to explain a decision if you can produce a report that said it was the right one.

*To stall.* One of the best ways to delay a decision is to postpone it by suggesting that it can be studied further.

*Legal.* An increasing amount of research is related to legal issues, such as claim substantiation and trademark infringement. Also, deceptive advertising complaints to the Federal Trade Commission create a demand for marketing research studies.

*PR/advertising.* Research often serves as the basis for advertising claims (e.g., “7 of 10 doctors . . .”). Here its role is to convince consumers either of the truth of a particular claim or of the trustworthiness and high-mindedness of the company in general.

*Consciousness raising.* In some cases, conducting a study is designed to focus attention of either respondents or interviewers on a topic. For example, a manager at a major computer manufacturer used a customer survey as a way of increasing the sensitivity of the sales force to particular nontechnical benefits and problems from the customer’s perspective.
TABLE 2.1 Different Uses of Information

1. To help make a decision
   a) Accurate use (use that accepts the results as relevant)
   b) Inaccurate/biased use (selective use to support a position)
2. To gain knowledge
   a) Content (specific knowledge from the study)
   b) Process (general knowledge about procedures, customers, etc.)
3. For political purposes
   a) Include others in the process
   b) Tradition/policy
   c) Signal importance
   d) Delay a decision
   e) Impress others
4. To increase comfort
   a) Reduce uncertainty about a decision
   b) Feel did a thorough job

One typology of information use, based on Menon and Varadarajan (1992), stresses the intended use (Table 2.1). They draw a distinction between use for decision making versus use for the decision makers (e.g., for knowledge/learning, comfort/uncertainty reduction, or political purposes). Menon and Wilcox (1994) have developed a scale to measure the use of market research. Based on their analysis, they break use into six categories:

1. Congruous (consistent with the results)
2. Incongruous (inconsistent with the results)
3. Cynical (for appearance or political reasons)
4. Positive (to draw attention to the area)
5. Process (learning because of participating)
6. Product (specific learning)

WHAT IS WORTH RESEARCHING

One perspective on what is worth researching comes from the Marketing Science Institute (MSI). A foundation with over 60 corporate member firms, MSI is dedicated to encouraging research by academics on topics that are relevant to practice. Every two years, it prepares a statement of research priorities based primarily on practitioners’ views. The 1996–98 (Table 2.2) priorities indicate interest in fairly broad strategic issues (e.g., really new products, long-term customer relations, the impact of information technology). While the standard topics of advertising and pricing are relevant, it is clear that the practitioners (of whom the largest subgroup is in the market research function) view the potential of marketing research to be greater than simply testing elements of the marketing mix.
TABLE 2.2 1996–98 MSI Research Priorities

1. Customers and Consumers
2. Innovation and Really New Products and Markets
3. Information Technology and New Media
4. Marketing Management Organization and Processes
5. Global Marketing
6. Management Use of Information and Market Research
7. Brand Equity and Product and Brand Management
8. Marketing Measurement, Engineering, and Empirical Generalization
9. Pricing and Promotions
10. Service
11. Channels and Sales/Value Chain
12. Understanding Competition
13. Market Orientation
14. Marketing Communications
15. Public Issues

Another perspective comes from recognizing the imperfect understanding of even experts. For example, Hock (1988) found that marketing experts were no better than ordinary consumers in predicting general consumer opinions—and neither was very good. Consequently, one might assume we know less than we think we do and hence more is worth researching than we think.

INFLUENCES ON INFORMATION USE

The likelihood that managers pay attention to research findings depends on several factors. One study (Deshpandé and Zaltman, 1982) found that research that had impact tended to:

- Be confirmatory rather than exploratory in nature
- Not produce surprising results (see also Lee, Acito, and Day, 1987)
- Occur in a decentralized organization
- Have a high level of interactions between researchers and managers
- Be of high technical quality

In a follow-up study focusing on industrial firms, Deshpandé and Zaltman (1987) again confirmed that surprising findings are less utilized (confirming the obvious but often overlooked fact that new ideas are rarely welcomed). They also found greater utilization in more formal organizations when the objective was more exploratory.

Perkins and Rao (1990) studied the use of information in a controlled setting and found that more experienced managers relied more on "soft" information, particularly when the decision was less structured or routine. Maltz and Kohli (1995) studied the
dissemination of information from marketing to other functions. They found that information use is influenced by research quality (measured by its accuracy, relevance, clarity, and timeliness), which in turn is influenced by confidence in the researchers (their trustworthiness and competence).

The role of trust has received considerable attention. Studying interactions between 779 providers and users of market research including intra- and intercompany relationships, Moorman, Zaltman, and Deshpandé (1992) found that personal trust and perceived quality of interaction were the main determinants of information use. Further, the impact of trust tended to be indirect, influencing the perceived quality of interactions between research users and providers, which in turn influenced information use. Interaction quality was measured in terms of (a) handling of disagreements, (b) insight production, (c) strategic understanding, (d) customer orientation, and (e) productive interaction. Trust is enhanced most by the (a) integrity and also by the (b) confidentiality, (c) sincerity, (d) tactfulness, and (e) timeliness (including honesty in making promises) of the researcher. Interestingly, congeniality actually led to decreased trust. In addition, the researcher's expertise (training and experience) and willingness to reduce uncertainty (interpret inconclusive data) contribute to trust (Moorman, Deshpandé, and Zaltman, 1993a,b).

The continual flow of information makes it likely that firms will frequently deviate from or change plans. Moorman and Miner (1995) suggest that the availability of real-time information increases both organizational improvisation and its effectiveness when knowledge of past information (i.e., organizational memory) is high.

Specific issues of information use also arise. The massive amounts of scanner data available motivated a conference on “Building an Information Strategy for Scanner Data” (Weinberg, 1989). Goldstein (1993) studied the use of scanner data by product managers. He concluded that managers organize their knowledge as a series of stories, which they update in the light of unexpected results. Also interestingly, analysis tended to be simple and based on limited data rather than extensive statistical analysis of available data.

In a more qualitative vein, Zaltman (1989) focused on the relationships between advertising agencies and their clients. He found a tendency to focus on evaluative rather than developmental research and to use only convenient measures of effect (e.g., awareness rather than the interaction effect of advertising on price elasticity). One conclusion reached was that a market research group should be attached to each major marketing unit and its charter should be broad.

THE VALUE OF INFORMATION FOR DECISION MAKING

In valuing research this way, we take a basically “transactional” view. That is, we view information in the context of a single decision. Clearly, this understates the value if any general knowledge is generated that is then applied in future situations. Further, as discussed earlier, there are many uses of information that don't relate to decision making per se (e.g., political uses). Here, we narrow the focus and present a framework for assessing the value of information in terms of making a single decision.

There are many decisions where the situation is sufficiently clear that no additional information is likely to change the decision, and hence the value of information is very small. (For example, if the boss asks if you could work late, the answer is, “Yes.”) On the other hand, some decisions cry out for information that may not be available at any
price. (For example, secret information about the price of Polaroid stock six months in the future would be crucial to the decision whether to buy or sell the stock, except for certain legal issues.) More likely, however, is a situation where information will improve the odds of making a good decision (such as getting a better measure of the market potential for a new product).

The concept of the odds of making a good decision is crucial to the concept of the value of information. For example, assume that a decision maker is faced with a tough decision—one where there are two choices and each one seems about equally likely to be correct. By relying on experience, the decision maker might be able to increase the odds of choosing the correct action from 50:50 to 60:40. By collecting the best available information, the odds might be increased from 60:40 to 80:20 in favor of making the correct decision. Hence, the value of information in this case comes from increasing the chance of the correct decision from three out of five to four out of five. Information is not perfect (there is still a one in five chance of making a wrong decision), and in fact it is possible that we will make the wrong decision after collecting information, whereas we would have made the correct decision without the information. Still, over the long run, one is clearly better off with information than without it whenever there is uncertainty about the consequences of alternative decisions.

Another point worth making is that unless a decision changes as the result of information, the information has no value in this context. This truism has two separate levels of meaning. First, unless the manager is willing to change his or her mind based on data, the data collection is an unnecessary expense. Second, if all the decisions after information collection are to go ahead and the prior decision was also to go ahead, the information has no value. For example, it could be relatively obvious that we wish to enter a market. If we collected further information, we might better pinpoint the size of the market. However, we would be unlikely to find a market that would alter the enter/not enter decision, so the information would not be worth anything. This leads to two other key points. In general, information is most useful in cases (a) where we are most unsure what to do and (b) where there are extreme values (either huge losses or profits), which would be extremely important if they came to pass. What collecting information really does is lower the odds that you will go ahead with a flop or, conversely, fail to proceed with a success. Exactly how much information is worth depends on the following three things:

1. The amount the odds of making the correct decision increase when the information is collected and used
2. The relative benefit (profitability) of the alternative decisions
3. The cost of the information

This chapter presents a formal framework for decision making and for evaluating the worth of information. While this framework is rarely used formally, both the logical structure itself and concepts concerning the value of information underlie the decision to collect information. The chapter closes by reemphasizing some real-world considerations in assessing the value of information. The reader is warned that the treatment that follows is at least semiformal. If such treatment leads to intimidation or frustration, the reader should concentrate on understanding the concept of the value of information, as this is by far the most important concept in the chapter.
DECISION ANALYSIS AND INFORMATION VALUE: CONCEPT

Before discussing decision analysis and the value of information in detail, it is useful to highlight the concepts by considering the case of whether to introduce a new product. New product introduction is a risky undertaking, with the risk varying by, among other things, the level of study prior to entering the market, the relative benefits and costs of the new product versus the products it competes with, and the general level of competitive activity.

In structuring the decision, one first needs to identify the possible alternatives. Here, we will assume the possible decisions are to go ahead and introduce the product, to not introduce the product, or to conduct a test of the product and then either go ahead or not. Next, we need to specify the possible results. While clearly there are an infinite number of results (e.g., sales = 0 units, 1 unit, 2 units, ...), we can (over)simplify this by considering only two levels of sales: low and high.

The consequences of the various combinations of decisions and market results are pretty obvious. Introducing the product to a low sales level leads to a loss, while introducing it to a high level leads to a profit. Not proceeding has no cost or profit associated with it. Performing the test adds to the cost.

Notice that we are ignoring the very real possibility that the study would uncover information that would allow us to improve a product and thus improve the chances of a high sales level. This simplification is made solely to prevent the discussion from becoming any more complicated than it already is.

We now need to assess how likely each of the possible results is. In this case, we begin by assuming that the likelihood of a successful new product is so low that, if we directly introduce the product, sales are more likely to be low than high (i.e., the likelihood of low sales is high and high sales is low). Next, we consider how likely a test is to produce a positive result. Since, at least for most new products that are similar to existing ones, test results are likely to be better than eventual market results, we assume the likelihoods of negative or positive results are both about 50 percent. Assuming we get a negative result, we know from experience that the chances of a low sales level are very high and those of a high sales level very low. On the other hand, if we get a positive result we have learned that there is a moderate chance of then achieving either a low or high level of sales.

This information is summarized in the tree in Figure 2.1. The viable decisions are thus pretty clear: don’t introduce, introduce without testing, or test and proceed to introduce if the test result is positive (it generally makes no sense to test and ignore the results, which going ahead after a negative test would imply). The impact of these decisions can be summarized as follows:

Do not introduce. You are certain that there will be no impact (loss or profit).

Introduce without test. The likelihood is high you will incur a loss and low you will produce a profit.

Test. There is about a 50 percent chance you will introduce the product with a moderate chance of a loss and a moderate chance of a gain, and a 50 percent chance you will decide, based on the negative test result, not to introduce the product. You are certain you have to pay for the test.
FIGURE 2.1
Conceptual Example: Product Introduction and Testing

What this informal decision analysis does is structure the discussion about decisions around possible events, consequences, and likelihoods, rather than preferences. For example, faced with this decision most people would, if they did not test, prefer not to introduce the product. The decision to test would then be based on whether the decision maker(s) preferred a certain result of no net income or to pay for the test and have a 50 percent chance of no net income and a 50 percent chance of either a loss or a profit (which is basically a 50 percent chance of no income, a 25 percent chance of a loss, and a 25 percent chance of a gain). The difference in the value of the result if the test was run and the value without the test is then the value of the test (soon to be called the value of information).

DECISION ANALYSIS

In this section, we discuss decision analysis as a way to structure decision making. The term decision analysis refers to a logical framework for choosing among alternative courses of action. Much has been written on the subject (Assmus, 1977; MaGee, 1964; Raiffa, 1968; Schlaiffer, 1959) including a fairly readable book by Jones (1977). The frame-
work is typically visualized in terms of a tree diagram (Figure 2.1). The typical method of constructing such a tree is as follows:

1. Delineate the possible courses of action.
2. List the possible results ("states of nature") of each course of action.
3. Estimate the payoff (usually in monetary terms) of each possible combination of courses of action and results.
4. Assign likelihoods of occurrence (probabilities) to the different possible results for each given course of action.
5. Select the course of action that seems to lead to the most desirable results.

Example

To see how decision analysis is used more formally, consider the following problem: The XYZ Transportation Company, which specializes in freight deliveries, is considering a new rate on its New York to Paris route. In the past, there has been a two-tier pricing system for one-pound packages: $20 for “first class,” which guarantees next-day delivery, and $10 for “regular,” which typically takes two to three days. We are now considering instituting a same-day delivery service at the price of $30 or $40 (we have a thing about prices in $10 increments and will consider no other prices—boss’s orders). After some preliminary analysis, we decide that one of three possible results is likely to occur if we price at $30: getting 100, 60, or 20 new packages per day. Similarly, if we price at $40, we can get either 50, 30, or 5 new packages per day.

Also, at the new prices we expect some of our present customers to trade up to the new service. At the $30 price, we think either 20 or 30 packages per day will be sent same-day instead of first class, whereas at $40, either 10 or 20 will move to same-day.

The daily cost of setting up and running the new service will be $700. The variable costs to send a package by the three classes of service are $18 for same-day, $12 for first class, and $8 for regular. What should we do?

Even though this is a fairly simple situation, the data are sufficiently extensive to make analyzing the decision in one’s head fairly complicated. Hence, to provide a structure to the decision-making process, one could quite logically begin by drawing a tree to represent it (Figure 2.2).

Having delineated the situation faced by identifying (a) the courses of action and (b) the possible results (outcomes), one would now proceed to estimate (c) the monetary consequences of each of the possible results. Consider the value of a single new piece of business at the $30 price. Since XYZ gets $30 and it costs them $18, they gain $12 for each new piece of business. Similarly, for everyone who trades up, they make $12 instead of $20 - $12 = $8, for a net gain of $4. Hence, for the result of 20 new packages plus 20 trade-ups, they would make incrementally $20 \times $12 + 20 \times $4 = $320 per day. When the fixed cost of $700 per day is figured in, the incremental profit becomes $320 - $700 = -$380. (Note here that we are using the incremental profit compared with doing nothing. We could also have calculated actual profit; we chose incremental because, quite frankly, the numbers are smaller.) One can get the profit results for each of the profit combinations in a similar manner (Table 2.3).

Having identified the profit implications of the various results, the next step is to estimate the relative likelihoods of the different possible results. This is typically done
FIGURE 2.2
Package Pricing Decision Tree

<table>
<thead>
<tr>
<th>Course of Action; New Service Price</th>
<th>Result: New Business</th>
<th>Result: Trade-Up Business</th>
<th>Incremental Daily Profit*</th>
</tr>
</thead>
<tbody>
<tr>
<td>None</td>
<td>—</td>
<td>—</td>
<td>0</td>
</tr>
<tr>
<td>$30</td>
<td>20</td>
<td>20</td>
<td>320 - 700 = - 380</td>
</tr>
<tr>
<td></td>
<td></td>
<td>30</td>
<td>360 - 700 = - 340</td>
</tr>
<tr>
<td></td>
<td></td>
<td>60</td>
<td>800 - 700 = 100</td>
</tr>
<tr>
<td></td>
<td></td>
<td>30</td>
<td>840 - 700 = 140</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>20</td>
<td>1,280 - 700 = 580</td>
</tr>
<tr>
<td></td>
<td></td>
<td>30</td>
<td>1,320 - 700 = 620</td>
</tr>
<tr>
<td>$40</td>
<td>5</td>
<td>10</td>
<td>250 - 700 = - 450</td>
</tr>
<tr>
<td></td>
<td></td>
<td>20</td>
<td>390 - 700 = - 310</td>
</tr>
<tr>
<td></td>
<td></td>
<td>10</td>
<td>800 - 700 = 100</td>
</tr>
<tr>
<td></td>
<td></td>
<td>20</td>
<td>940 - 700 = 240</td>
</tr>
<tr>
<td></td>
<td>50</td>
<td>10</td>
<td>1,240 - 700 = 540</td>
</tr>
<tr>
<td></td>
<td></td>
<td>20</td>
<td>1,380 - 700 = 680</td>
</tr>
</tbody>
</table>

*For the $30 price, incremental profit is $12 x New business + $4 x Trade-up business - $700; whereas for $40, incremental profit is $22 x New business + $14 x Trade-up business - $700.
by assigning probabilities to each of the possible branches of the tree. These probabilities may be based on survey results, experience in analogous situations, or expert judgment. In the present situation, assume that the probabilities of the different possible levels of new business for the $30 price are 20 units, .2; 60 units, .5; and 100 units, .3. Also assume the trade-up business probabilities are 20 units, .6; and 30 units, .4. For the $40 price, the probabilities of new business are 5 units, .2; 30 units, .6; and 50 units, .2. The trade-up business probabilities are 10 units, .5; and 20 units, .5. The decision tree can then be redrawn with the appropriate probabilities and profits (Figure 2.3).

To estimate the probability of a particular profit for a given course of action, simply multiply the probabilities of the results that must occur to produce the profit result. For example, 20 new packages and 20 trade-ups produce an incremental profit of $-380. The probability of the result of 20 new and 20 trade-up packages for a $30 price is .2 × .6 = .12.

Thus, each course of action produces a distribution of possible profits with probabilities attached to them (Table 2.4). Hence, the decision about which course of action

![Figure 2.3: Package Pricing Decision Tree with Probabilities and Profits](image-url)
Table 2.4 Profit Distributions for Three Possible Courses of Action

<table>
<thead>
<tr>
<th>Course of Action</th>
<th>Incremental Profit</th>
<th>Probability of Profit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Do nothing</td>
<td>0</td>
<td>1.00</td>
</tr>
<tr>
<td>Institute new service at $30</td>
<td>-380</td>
<td>.12</td>
</tr>
<tr>
<td></td>
<td>-340</td>
<td>.08</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>.30</td>
</tr>
<tr>
<td></td>
<td>140</td>
<td>.20</td>
</tr>
<tr>
<td></td>
<td>580</td>
<td>.18</td>
</tr>
<tr>
<td></td>
<td>520</td>
<td>.12</td>
</tr>
<tr>
<td>Institute new service at $40</td>
<td>-450</td>
<td>.10</td>
</tr>
<tr>
<td></td>
<td>-310</td>
<td>.10</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>.30</td>
</tr>
<tr>
<td></td>
<td>240</td>
<td>.30</td>
</tr>
<tr>
<td></td>
<td>540</td>
<td>.10</td>
</tr>
<tr>
<td></td>
<td>580</td>
<td>.10</td>
</tr>
</tbody>
</table>

to take has been converted to a decision about which distribution of results is more appealing. Several selection procedures are possible. Three of the most common are:

1. Choose the decision that guarantees the best result if everything goes wrong. This criterion (known as minimax) is the most conservative procedure and leads to very conservative decisions—in this case, doing nothing since both the other decisions could lose money and doing nothing would not.

2. Choose the decision that gives the chance for the best possible result. This is the gamble strategy (called maximax), which explains why people are willing to buy lottery tickets—they are willing to expect to lose a little money on the chance they will earn a lot. Since the $40 price offers the greatest potential gain ($680 if 50 packages and 20 trade-ups are generated), the new service would be instituted at a $40 price under this criterion.

3. Choose the course of action that provides the largest expected monetary reward. This is the criterion most often associated with decision trees (although not necessarily the best one). It requires calculating the expected monetary consequences of each of the possible courses of action by “weighting” the possible monetary results by their probabilities of occurrence. In the present example, this involves the following:

a. Do nothing and make $0 incremental profit.
b. Institute the new service at $30 and expect to make $164 per day incremental profit (Table 2.5).
c. Institute the new service at $40 and expect to make $148 per day incremental profit (Table 2.6).

Since the $164 per day net incremental profit from instituting the service at the $30 price is the maximum of the three possibilities, we would institute the new service at $30.
TABLE 2.5 Expected Incremental Profit of $30 Price

<table>
<thead>
<tr>
<th>New Business</th>
<th>Trade-Up Business</th>
<th>(A) Increment in Daily Profit: IP</th>
<th>R</th>
<th>(B) Probability of Result: P(R)</th>
<th>(A) \times (B)</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>20</td>
<td>380</td>
<td>.12</td>
<td>$ - 45.60</td>
<td></td>
</tr>
<tr>
<td>30</td>
<td>30</td>
<td>340</td>
<td>.08</td>
<td>$ - 27.20</td>
<td></td>
</tr>
<tr>
<td>60</td>
<td>20</td>
<td>100</td>
<td>.30</td>
<td>+ 30.00</td>
<td></td>
</tr>
<tr>
<td>30</td>
<td>140</td>
<td>18.0</td>
<td>.20</td>
<td>+ 28.00</td>
<td></td>
</tr>
<tr>
<td>100</td>
<td>20</td>
<td>580</td>
<td>.18</td>
<td>+ 104.40</td>
<td></td>
</tr>
<tr>
<td>30</td>
<td>620</td>
<td>12.0</td>
<td>.12</td>
<td>+ 74.40</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$ 164.00</td>
<td></td>
</tr>
</tbody>
</table>

Problems with Using Decision Trees

Decision analysis has been around for a long time, and its pros and cons are fairly well known (MaGee, 1964; Villani and Morrison, 1976). There are a number of problems inherent in using decision trees, which are discussed in this section.

Specifying the Alternative Courses of Action and Their Consequences In many situations, the alternatives are fairly clear-cut. For example, the vending machine companies' options in pricing are pretty much limited to 5-cent increments, given the equipment already in place. Similarly, a product manager at some stage may be faced with a choice between launching a new product nationally or regionally, test marketing it, doing further tests or refinements, or dropping it. What makes things complicated is the possible responses of competition or, as is becoming more important, regulatory bodies or lobbying groups. Since these responses can affect both the results (i.e., if a rate case finds against a utility, they can't raise rates) and their profitability (beating back consumer or competitive challenges is expensive), these potential responses can greatly complicate the tree. Even in the example used in this chapter, we would expect some probability that the rate would not be approved by some relevant regulatory agency and a good likelihood that competition would react to the new service in some way. These would in turn

TABLE 2.6 Expected Incremental Profit of $40 Price

<table>
<thead>
<tr>
<th>New Business</th>
<th>Trade-Up Business</th>
<th>(A) Increment in Daily Profit: IP</th>
<th>R</th>
<th>(B) Probability of Result: P(R)</th>
<th>(A) \times (B)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>10</td>
<td>450</td>
<td>.10</td>
<td>$ - 45.00</td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>20</td>
<td>310</td>
<td>.10</td>
<td>$ - 31.00</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>10</td>
<td>100</td>
<td>.30</td>
<td>+ 30.00</td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>240</td>
<td>.30</td>
<td>+ 72.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>50</td>
<td>10</td>
<td>540</td>
<td>.10</td>
<td>+ 54.00</td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>680</td>
<td>.10</td>
<td>+ 68.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$ 148.00</td>
<td></td>
</tr>
</tbody>
</table>
lead to further actions by XYZ Co. In short, a series of courses of action and results are needed to realistically represent most decisions.

Finally, it is important to recognize that for a "real" problem, no single tree is drawn. Rather, a first-cut tree is constructed to select those alternatives that seem most promising. Then, the other branches of the tree are dropped and those that are retained are refined, sometimes by collecting data, until the "best" decision emerges.

**Estimating Possible Results and Their Probabilities** There are three basic sources of the possible results of a decision and their probabilities: logic/deduction, past experience/empirical evidence, and subjective estimates.

1. **Logic/deduction.** In certain very simple situations, it is possible to deduce the probabilities of the results from the situation. For example, the probability of a head on the flip of a coin, a 7 on the roll of two dice, or a full house in a game of poker can be deduced from the situation and a few basic rules of probability and statistics (although students have a disarming tendency to do so incorrectly on tests). Unfortunately, in most marketing research situations this method is not applicable.

2. **Past experience/empirical evidence.** Past experience is one source of estimates of the possible results and their probabilities. When Procter and Gamble introduces a new soap, it has a pretty sound idea of possible sales levels because it has introduced so many similar products in the past. Similarly, data analysis is often performed and sales levels forecast based on models using such variables as GDP, market growth rate, and so forth. The models in turn can be used to formally generate the probabilities of different results. Unfortunately, the past data and analyses rarely seem perfectly compatible with the situation under consideration. Hence the analysis of past data typically only serves as a basis for subjective estimates of the possible results and their probabilities.

3. **Subjective estimates.** In the absence of hard data, a manager must make guesses about what the results will be. While these guesses should be based on as much analysis and experience as possible, they still involve some subjectivity. It is this subjectivity that, for many people, causes the greatest consternation over the use of decision analysis.

The first major issue in obtaining subjective estimates of the possible results and their probabilities is to decide from whom to collect the estimates. Aside from the obvious—finding someone who is knowledgeable, honest, and willing to provide estimates—knowing exactly who to talk to is something of an art. One obvious source is salespersons who are in direct contact with buyers and hopefully (but not always actually) in tune with the market. Another source is so-called experts, both inside and outside the organization. Since the responsibility for the decision under consideration will ultimately fall on someone, however, it is appropriate to involve the person or persons (i.e., the product manager) whose evaluation depends on the decision in estimating possible results and their probabilities. (A side benefit of this is that those people who give estimates will be involved in the analysis and, therefore, more committed to the results. This benefit can, of course, turn into a cost if individuals involved give false probabilities to affect the outcome of the analysis.)

The second major issue in assessing the possible results and their probabilities is how to obtain them. This turns out to be a very tricky task since most people don't
understand probability concepts (Tversky and Kahneman, 1974). The most obvious approach is to directly ask an individual to list the possible results and their probabilities of occurring. Unfortunately, many people (and especially nonquantitatively oriented managers) don’t respond well to such direct assessments of probabilities; and when they do respond, they are often inaccurate (Russo and Schoemaker, 1990; Bazerman, 1994). Hence, a variety of devices are employed to get the probabilities less directly.

The most commonly used gambit to elicit probabilities involves asking an individual to indicate various levels that sales will exceed with a certain likelihood. For example, the individual might be asked to indicate:

1. What level will sales exceed 90 percent of the time? (e.g., 5,000 units)
2. What level will sales exceed 50 percent of the time? (e.g., 10,000 units)
3. What level will sales exceed only 10 percent of the time? (e.g., 20,000 units)

By using the answers to these questions, a researcher can develop an entire distribution of possible results (Figure 2.4).

Alternatively, a researcher may ask a key individual to first list some possible results. Then, the researcher can ask the individual to indicate the relative likelihood of occurrence (from which probabilities of the results can be deduced). Detailed discussion of methods for eliciting results and their probabilities is beyond the scope of this book. For further reading, see Hogarth, 1975; Jones, 1977; Sarin, 1978; Savage, 1971; Winkler, 1967a,b.

Considerable opposition exists to using subjective probabilities. This comes from two basic schools of thought. The first position of opposition is that anything based on subjective probabilities is essentially worthless. Assuming the person making the estimates has experience, the subjective estimates will in fact be based on data (experience in analogous situations, etc.). The difference between subjective and data-based estimates (which should be and typically are subjectively adjusted) is thus not as great as it first appears. The other major opposition to using subjective probabilities is that since they are not perfectly accurate or easy to obtain, they are not worthwhile. Development of the probabilities of results is a nontrivial task. It is, however, doable.

**FIGURE 2.4**
Derived Distribution of Possible Sales Levels
Assessing the Monetary Consequences of Different Results  While this is possibly the easiest of the problems to deal with, it is by no means trivial. For example, estimating future costs of production given changes in energy costs, raw material prices, and so forth, is very difficult. Hence, the monetary consequences are really estimates; their effect on the decisions should usually be checked at least by sensitivity analysis if not by incorporating multiple monetary results and attendant probabilities into the decision tree.

Choosing an Appropriate Criterion  The most obvious criterion to apply is expected monetary value. This, though, is a good criterion to use only in the case of repetitive decisions that are independent of each other and when the outcomes are not so large as to greatly affect the organization. The independence notion is rarely true, since the condition of the general economy alone dictates that either most things go well or many go sour together. Also, in many cases the decision will have a sufficiently large impact that it will affect the organization, or at least the part with which the decision maker is associated. For example, certain possible results may seriously damage the financial position of the company, and decisions leading to these will typically be avoided in going concerns.

Another barrier to the expected value criterion is individual behavior. Since turning a profitable product into an unprofitable one may lead to being fired, whereas doubling profits may only lead to a 10 percent raise, the personal consequences of the results may be asymmetric and, hence, the expected value criterion inappropriate. In short, individuals may be understandably more cautious (risk averse) than is implied by the expected value criterion.

It is possible to develop a formula that translates the different monetary results into utilities and then to compute expected utilities. A more pragmatic approach, however, is to calculate the expected value and the range of possible results and then check to see if any of the likely results of the indicated decision are sufficiently bad to cause reconsideration and possibly a change to a less risky decision. It is also sometimes appropriate to check other decisions that result in lower expected values to see if there is a possible result under these decisions that is so desirable it is worth going against averages.

Sensitivity Analysis

Given that any decision tree is typically at best a facsimile of the world, it is useful to examine the sensitivity of a decision to small changes in the tree. For example, would changing the new business demand estimates in Figure 2.3 change the decision? If changing the estimates in the tree does not change the decision, then the decision is relatively insensitive to those estimates, giving one more confidence that the decision is optimal. If, on the other hand, the decision changes as a result of small changes in the tree, then it is less easy to argue strongly that the optimal decision is known.

Whenever sensitivity analysis reveals something on which a decision does seem to depend, it suggests that this type of information is relatively crucial and is possibly worth further investigation. Put more simply, if a decision is portrayed as a tree, then those pieces of information that seem to affect the decision are the ones that should be further studied. While this sounds obvious, many dollars have been spent fine-tuning
advertising copy when the major uncertainty was the possible entrance of a new competitor or a ban by the FDA. Hence, one should generally study those elements of a decision that (a) matter (no sense studying irrelevant material, as any student knows), (b) are uncertain (no sense studying something that is already known), and (c) can be learned about (if you can’t reasonably expect to reduce uncertainty, it is not very intelligent to spend much money trying to do so).

Summary

Having spent considerable time pointing out the weaknesses of decision trees, it is important to indicate that they still are useful devices. Their major advantage is that they provide structure in what appear to be largely unstructured situations. It seems far more constructive to have people debating the likely results in sales of a decision, rather than arguing whether they like the decision or not. (Such discussions are also more likely to be based on facts than on political clout or debating skills.) There is also some evidence that suggests that breaking a decision into small parts leads to better decisions. Decision trees also provide an indication of what key uncertainties exist. If the expected value criterion is used, it provides a very useful starting point for deciding what to do. In short, given an uncertain world, decision trees are a useful device for structuring a problem and getting an indication (relatively quickly and inexpensively) of what is the best decision to make. Since managers are ultimately judged more by results than by method, however, it is the managers’ prerogative to make choices any way they choose.

VALUE OF INFORMATION: QUANTITATIVE ASSESSMENT

Before investing time and money in collecting information about a decision, most people make a judgment (at least implicitly) on whether the information will be worth the trouble. Consider, for example, an individual choosing a new dishwasher. That person may already have a choice in mind (e.g., I have a GE now that I bought from store A and it worked well, so I will buy a GE there next time). In deciding whether to gather more information (e.g., read Consumer Reports, comparison shop), several major considerations exist:

1. Under what kind of time pressure is the individual? (Is the present dishwasher flooding the kitchen or just getting old? How much “free” time does the individual have?)
2. How easy is it to collect more information? (Does the individual subscribe to Consumer Reports, live in an area where shopping is easy, etc.?)
3. What is the cost of a bad decision? (What is the cost of buying another new machine, cost of a service contract, etc.?)
4. How different are the available alternatives? (Does which brand is bought make much difference in either length of life or quality of service?)
5. How likely is it that more information will change the decision? (If the individual is fairly certain that he or she will buy a GE at store A, then more information is probably irrelevant.)

Of these considerations, 1 and 2 are related to the cost of information, 3 and 4 to the relative results of the alternative decisions, and 5 to the relative odds of making a
good decision with and without more information. If a sample of people were asked whether they would collect information in a set of situations/scenarios, we would expect more of them to collect information when (a) the cost of information was low, (b) there was a noticeable difference among alternatives, and (c) they felt a relatively high degree of uncertainty about which decision alternative to select.

While the preceding seems sensible, it does not directly produce a quantitative assessment of the value of additional information. To get a quantitative assessment, one procedure uses decision trees. The procedure has three basic steps:

1. Build a decision tree for the situation assuming current information. Then calculate the optimal decision and its expected value (EV|Cl).
2. Build a decision tree for the situation assuming that additional information were available. Then calculate the optimal decision given the additional information and its expected value (EV|AI).
3. Estimate the expected value of additional information (EVAI) as EVAI = EV|AI − EV|Cl. Hence, the value of information is the expected improvement in profit that would result if the information were obtained.

Example

A more complete discussion of the methodology appears in the appendix to this chapter. However, for illustrative purposes a simpler example will be used here. Assume a product manager is trying to decide whether to continue selling the old formulation of a product and end up with essentially certain profits of $50 or switch to a new one, which will end up with profits of either $10 or $80 (e.g., the decision on New Coke). It seems equally likely it will produce $10 or $80 given current information. Hence, we get the picture in Figure 2.5. The expected values of the two decisions are as follows:

Continue selling old formulation: $50(1.0) = $50
Sell the new formula: $10(.5) + $80(.5) = $45

Therefore, given current information, we would keep the old formulation and EV|CI = $50.

Now assume we could get a research report on market acceptance of the new formulation, which would be either unfavorable (in which case the probability that the prof-

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**FIGURE 2.5**
Decision Tree with Current Information

Decision

- Old formula
- New formula

(1.0)
(0.5)
(0.5)

Results

- $50
- $10
- $80
it would be $10 increases to .66) or favorable (in which case the probability that the
profit would be $10 decreases to .26). Also assume that we expect the probability of
an unfavorable report to be .60. We can represent the choices given this additional in-
formation by Figure 2.6.

The results of the two decisions under the two possible research reports are deter-
mined as follows:

Unfavorable report:

Old formula: $50(1.0) = $50
New formula: $10(.66) + $80(.34) = $33.80

Favorable report:

Old formula: $50(1.0) = $50
New formula: $10(.26) + $80(.74) = $61.80

Hence, given an unfavorable report, we would, not surprisingly, keep the old for-

tula and make $50; while given a favorable report we would use the new formula and
expect to make $61.80. Since 60 percent of the time we expect an unfavorable report,
the expected value given additional information is

\[ EV|AI = 50(.60) + 61.80(.40) \]
\[ = 54.72 \]

Thus, the expected value of the additional information (in this case, the research report)
is

\[ EVAI = EV|AI - EV|CI \]
\[ = 54.72 - 50.00 \]
\[ = 4.72 \]
This approach is relatively easy to extend to more complex situations. The problem in applying the approach comes in obtaining reasonable estimates for the monetary results that are possible, the probabilities of these results, the probabilities of the various possible results of additional information, and the probabilities of each of the actual results given the information. In many situations, these probabilities are hard to deduce even with considerable effort. For this and other reasons, it is often useful to calculate an upper limit on the value of additional information.

To calculate the upper limit on the value of information, two steps are employed:

1. Calculate the optimal decisions given perfect information (i.e., the decision you would make if you knew what the result would be in advance) and its expected value (EV|PI).
2. Calculate the expected value of perfect information (EVPI) as EVPI = EV|PI – EV|CI.

Returning to the example in Figure 2.5, we see that, if profits for the new formula would be $10, we would want to stick with the old formula (and make $50); whereas if profits for the new formula would be $80, then we would want to use the new formula. Since half the time the profit from the new formula will be $10 and half the time $80,

$$EV|PI = 50(.5) + 80(.5)$$

$$= 65$$

Hence,

$$EVPI = EV|PI - EV|CI$$

$$= 65 - 50$$

$$= 15$$

The most we would be willing to pay for information would be $15. If someone offered to sell us research for $20, we would politely decline the offer no matter how good the person’s forecasting record was.

**Problems in Assessing the Value of Information**

The methodology just described for quantitatively assessing the value of information, once learned, is relatively simple to apply. Its conceptual use is widespread. Yet its application in a formal sense is limited. There are several reasons for this limited use. They are as follows:

**Difficulty in Application** It is possible to argue that the technique is not used because it is perceived to be hard to apply. This argument is, however, both largely incorrect and self-serving. The cost of using such procedures is fairly low; and their level of use is even lower, indicating other explanations are needed.

**The Expected Value Criterion Does Not Apply** This limitation is an important one. For a small firm, operating on an expected value basis ignores the very real problem of
bankruptcy. Similarly, the job security of an individual may require avoidance of bad results more than attainment of spectacular ones.

**Prima Facie Decisions** Many apparent decisions may in fact be preordained. This can be because the situation dictates the decision (i.e., if I'm a small firm producing a commodity, I may have to match price cuts). Alternatively, it may be that political realities dictate a decision. (We may all know that the idea is dumb; but if it is the boss's pet idea, we may prefer to have the market test tell the boss so.)

**Company Policy** In many cases, it is company policy to proceed in a certain manner. For example, it may be policy to test commercials on samples of 100 in Albany, New York. Therefore, the value of information is not the issue—the only feasible course of action is to proceed. (It is, of course, possible to argue that the company policy is in need of revision. While this may make you a star, it is more likely to make you unpopular, unemployed, or both.)

**SUMMARY**

As discussed earlier, the value of information is related to several factors:

- **The accuracy of information.** Obviously the more accurate the information, the greater its value.
- **The cost (both dollar and time) of information.** Data already on hand or contracted for are relatively costless, whereas collecting new data is both costly and time consuming.
- **The ability and willingness to accept information and act accordingly.** The more receptive management is to information, the greater the value of the information.
- **The lack of clarity over what the right answer is.** The more obvious the decision, the less the need for information.
- **The extreme results and their consequences.** The more serious the extreme results are, the greater the need for information.
- **The degree of risk aversion on both a company and a personal level.** The greater the risk aversion, the greater the information need. On a personal level, getting the right information may protect one to some extent in case the decision is bad. (At least we can blame luck or some other factor rather than lack of diligence.)

**Competitive reaction to information gathering in terms of "jamming" the information and being given more time to plan a counterattack.** Competitors will often do their best to destroy the information value of data collection, especially test markets where tripling advertising, cutting price, and offering large trade deals to fill the channels of distribution are only a few of the common gambits. The motivation for this is to feed you bad information and make it harder for you to make the right decision. Also, the more time you
spend gathering data, the more obvious it becomes to competitors what you are planning to do and the more time they have to react to it.

*Company policy.* Company policy often dictates the "need" for information collection.

*The need to gain agreement.* Information collection is perhaps most important in that it facilitates the establishment of reasonable agreement among the many parties to a decision about the advisability of the decision and the way to proceed.

*The need to stall or build momentum.* Often, a decision is sufficiently controversial that people look for a way to postpone it. Opponents of a position who feel open opposition is unwise can and do line up in favor of gathering more data, a much less risky position. By the same logic, supporters of a proposal who believe they do not have sufficient support to push the proposal through at the present may suggest getting data (a "pilot" study) to determine feasibility as a means of getting a toe in the door.

Managers use information for a variety of reasons: to make decisions, for political ammunition, and to make themselves more comfortable with a course of action. All of these make information valuable. For example, being comfortable with a decision lends to pursuing it with great vigor, which in and of itself improves the odds of success. Focusing on information as a decision-making tool/aid, it is important to recognize that managers, like other humans, show evidence of a number of biases in judgment. Often referred to as context effects, or more generally behavioral decision theory, response to information is influenced by its presentation/context (cf. Bazerman, 1994; Russo and Schoemaker, 1990). For example, in addition to being overconfident in forecasts as mentioned in the introduction, managers tend to

1. "Anchor." In other words, once they have an opinion, they tend to hold on to it. One way they do this is to look for "confirming" information, that is, information that is consistent with their opinion.
2. Rely on "available" information. That is, they pay attention to information that is easily recalled. This is a variant on the "a picture is worth a thousand words" cliché, which suggests that vivid information is weighted more (too) heavily. Hence, a single comment in a focus group or a single experience with a product or customer may have a disproportionate effect on opinions/decisions.
3. Ignore "base rate." In many circumstances, the general population produces information that makes an event extremely likely (or unlikely), as well as some specific data that suggest a different outcome. People often rely too much on the specific "case" information in forming a judgment. Consider, for example, a father evaluating the possibility that his son will be a professional football lineman, of whom there are perhaps 350. The base information (350 out of thousands who play high school football) suggests the odds are low/essentially nil. On the other hand, the son is 6 feet 3 inches tall, 250 pounds, runs a 5.0 second 40-yard dash, and was all-county. The father is convinced the son will be an all-pro. While the son’s statistics are indeed encouraging and similar to those of many pro linemen, they are similar to those of many more couch potatoes. The father has ignored
the base rate, partly because he wants to believe the case information. Similarly, the conviction that a new product concept is a winner based on initial results often ignores the fact that even among new products that are introduced, most fail.

4. Misuse of information/feedback. In one study, the presence of accurate information actually decreased the performance of managers in a simulated market (Glazer, Steckel, and Winer, 1992).

The point here is not to discuss "behavioral decision making" in detail—indeed, there are many articles and books on the subject (cf. Bazerman, 1994). Rather, the point is simply to indicate that information may be used in nonoptimal ways by human beings, hence altering its value as well as its impact. Moreover, experienced managers may use different information from that used by inexperienced managers in new product promotion decisions. Perkins and Rao (1990) found experienced managers relied on more information in general and more "soft" information in particular. Hence, the same biases are unlikely to be evidenced by all decision makers or in all situations. In the extreme, data may be as much like an inkblot test ("What do you see in it?") as a "fact" to be analyzed clinically and statistically.

The formal determination of the value of information can be a fairly tricky task. Nonetheless, the concept of comparing the value of information with its cost is a useful step. In doing so, it is essential to define both benefits and costs broadly enough to take into account the positions and proclivities of the various parties to the decision. Based on the assumption that at least occasionally one will find information of positive value (a hoped-for result if those individuals in market research positions are to continue to eat), the rest of this book is devoted to alternative means of collecting, analyzing, and utilizing information.

**PROBLEMS**

1. Assume you were considering changing the formulation of a food product by substituting one ingredient for an existing one.
   a. List the concerns you would have.
   b. Draw a decision tree to represent the problem.

2. What do you think would be the value of additional information in each of the following situations:
   a. A decision by P&G about whether to market Tide next year.
   b. A decision about which style dial to put on GE dishwashers this year.
   c. A decision whether or not to drill an oil well.
   d. A decision to launch a new packaged goods product.
   e. A decision to change the format of a ballet company's performances.

3. Bernie C. owns an ice truck. He sells ice cream on his lunch hour. When the weather is good, hot, and humid, he can net about $120 per day at the beach or about $60 per day if he sells ice cream around his home. When the weather is poor, cold, and rainy, his net at the beach is about $15 per day, and at home about $25 per day.