CHAPTER 1

The Marketing Engineering Approach

A good decision requires a reasoned choice among competing alternatives. Good decision making is essential in business and does not happen by accident. Business leaders in today's unpredictable but data-rich decision environments who want to develop effective decision-making skills must learn the art and science of decision making and then apply those lessons in practice. This book is designed to help readers become more effective marketing decision makers by providing them with the necessary concepts and tools, as well as the opportunities to apply them.

Marketing managers make frequent decisions about product features, prices, distribution options, and sales incentives. In making these decisions, managers choose from among many alternative courses of action in a complex and uncertain world. Like most decisions, marketing decisions follow an intuitive decision-making process comprised of judgment calls based largely on managers' mental models of the world, developed through their own experiences. In many cases, such mental models, perhaps backed by market research data, may be all that managers need to feel confident about their decisions. Yet mental models are prone to systematic errors. Although everyone recognizes the value of experience, any experience is unique to each person and can be skewed toward particular points of view: Sales managers might lower advertising budgets to achieve higher personal selling expenditures, whereas advertising managers might prefer larger advertising budgets.

An alternative approach to making decisions about advertising expenditures can employ a spreadsheet decision model of how the market should respond to various expenditure levels. Managers can use this model to explore the sales and profit consequences of alternative expenditure levels before making a decision.

The systematic translation of data and knowledge (including judgment calls) into tools used for decision support is what we call **Marketing Engineering**. In contrast, when a decision maker relies solely on his or her mental model, without using any support system, we refer to it as **conceptual marketing**. A third option is to automate the decision process using a sophisticated information system, an increasingly popular approach we call **automated marketing**. However, the intrinsic complexity of many marketing problems defies easy solutions or automation; often, a combination of decision support tools and the judgment of the decision maker provides the best results. That is, approaches that systematically combine managerial judgment with formal decision models are **Marketing Engineering (ME)**: *a systematic approach to harness data and knowledge to drive effective marketing decision making and implementation through a technology-enabled and model-supported interactive decision process.* In an organizational setting, the ME approach requires the design and construction of decision models and the implementation of those models in the form of marketing management support systems (MMSSs).

Marketing Engineering: A systematic approach to harness data and knowledge to drive effective marketing decision making and implementation through a technology-enabled and model-supported decision process.

The purpose of ME is actually to simplify the decision context and create a decision architecture to help focus on the key issues. Without simplification, noise rather than insights drive people's decisions. A good decision model therefore focuses attention and limited resources on the decision at hand.

In addition, ME aids managers by providing a platform to ask "what if," enabling them to assess the **opportunity costs** associated with their decisions and determine the potential value of alternatives they choose to reject. For example, if a marketing manager must select between two pricing policies and chooses the lower-priced option, the ME approach can help assess the foregone profitability of the higher-priced option. This capability of ME is critical. In reality, managers can observe only the consequences of actions they have actually taken; however, ME helps them understand whether they might have made better decisions to begin with.

THE EMERGING MARKETING DECISION ENVIRONMENT

Although there have been attempts to employ aspects of ME in organizations since the 1950s, the pace has accelerated in the past decade, largely because of the range of technologies that make the approach imperative in competitive markets. Prior attempts to engineer marketing have generally led to short-lived successes, not because of poor models but because of the lack of technology available to embed that success into the fiber of the organization. During the past decade, technology has advanced to a stage that model-based decisions can be integral parts of the repertoire of skills marketing managers possess.

For several decades, researchers and practitioners have developed and implemented powerful systems that facilitate decision making in real-world marketing settings. Yet until recently, much of the knowledge about marketing decision models resided primarily in specialized academic journals or required considerable technical expertise to comprehend, making it available only with the help of specialized consultants. Major changes began with the development of stand-alone models, embedded within hundreds of commercially available software packages, that support marketing analytics. With the advent of enterprise-wide systems for resource planning (ERP) and customer relationship management (CRM), marketing analytics became an integrated aspect of the decision-making architectures that leading firms employ. As an indication of this trend, a 2005 IDC report projected annual growth of 4.5% in marketing automation applications during 2004–2009 (IDC 2005).

Exhibit 1.1 shows how the ME approach transforms objective and subjective data about the marketing environment into insights, decisions, and actions.

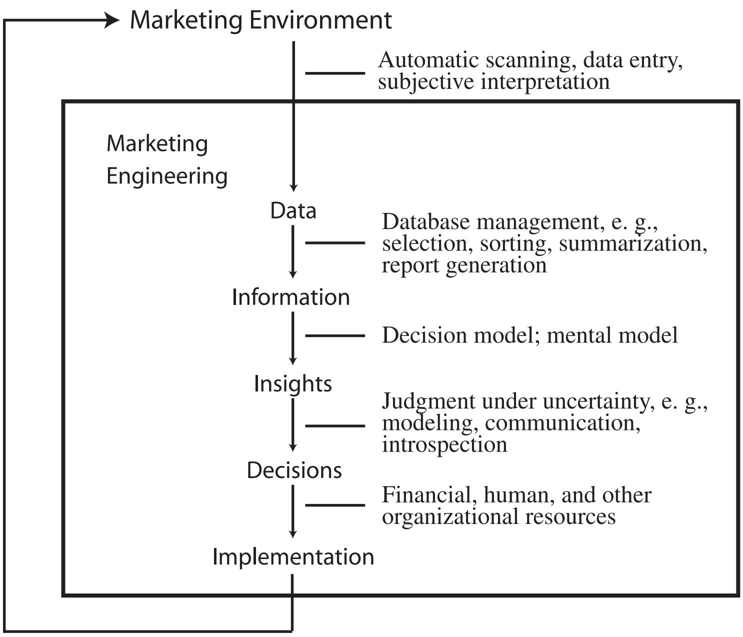


EXHIBIT 1.1
The Marketing Engineering approach to decision making helps transform objective and subjective data about the marketing environment into decisions and decision implementations.

Exhibit 1.2 sketches how ME can become an integral part of the information and decision architectures that support marketing decision making.

Trends that Favor Marketing Engineering

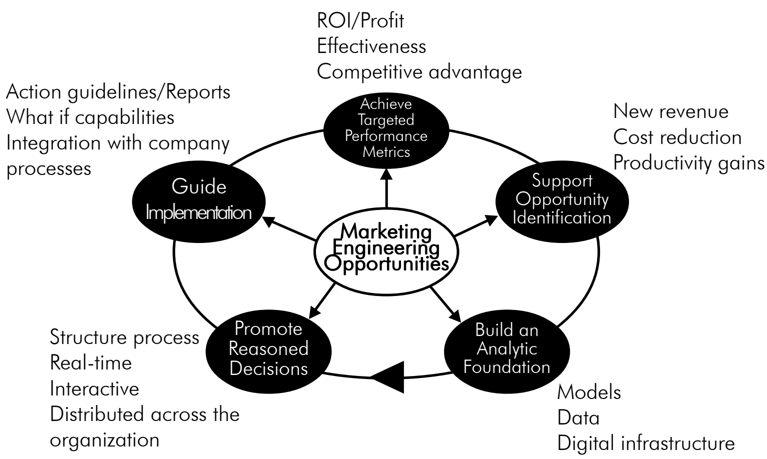
Although ME encompasses all the elements shown in Exhibits 1.1 and 1.2, in this book, we focus more narrowly on how Marketing Engineering helps transform data, information, and insights into effective decisions. Several trends, both on the supply side and the demand side, favor the wider acceptance of ME approaches among companies.

The ubiquity of high-powered personal computers connected to networks

Like other professionals, marketing managers depend increasingly on computers to perform their jobs. A senior marketing executive told us recently, "Ten years ago in my department, we had lots of people and very little software. Today we have lots of software and very few people." Computers are now networked with other computers through local area networks (LANs) and connected to external computers and databases all over the world via the Internet. For example, more than 400 million copies of Microsoft Excel currently are in use (*BusinessWeek* 2006). Excel, similar to other model-building software such as Java, enables companies to embed models into their information and decision systems, increasing their ability to gather, process, and share information and then apply marketing models at the point of decision making.

EXHIBIT 1.2

The ME approach offers several opportunities for using information technologies to apply a marketing decision environment throughout an organization. It supports the identification of new business opportunities, offers a common analytic foundation for driving marketing decisions, incorporates the latest insights and practices associated with a particular area of marketing decision making (e.g., segmentation), and integrates actions with decisions, all of which can serve to enhance strategically important metrics.



An exploding volume of data

The automatic electronic capture of data related to transactions with customers and the growth of interactions and exchange via the Internet have generated massive amounts of potentially useful information about the preferences and behavior of customers. In a sense, an abundance of data can be a bigger problem than a lack of data. It requires strong managerial skills, advanced analytical capabilities, sophisticated information technology, and superior organizational capabilities to transform these data into actionable marketing knowledge. Marketers demand decision tools and processes that can quickly transform data into insights and actions. Outdated data or analyses leave managers just as dependent on intuition and experience as in the past—and at a disadvantage compared with more nimble competitors.

Reengineering marketing

Today's firms use flat organizations, ad hoc teams, outsourcing, strategic relationships, and reduced cycle times. In this environment, firms are reengineering marketing functions, processes, and activities for the information age. In the reengineered firm, centralized decision making, a characteristic of traditional hierarchical organizations, is giving way to the decentralized decision making that is characteristic of entrepreneurial organizations. As a consequence, marketing managers increasingly deal directly with market information and use computers to complete tasks that were once done by support staff.

Higher standards of accountability

Several factors, including the pressures of the most recent recession, the increasing levels of competition in major markets, and the improved ability to associate market response with marketing activities (e.g., Direct TV, Web sites), have focused senior management's attention on marketing's contribution to the top and bottom lines. Senior management now demands that marketing expenditures be justified in the same way as other firm investments. A 2002 Accenture report indicates that total global marketing spending is about $1 trillion, but nearly 70% of the executives participating in the study did not know the return on investment (ROI) of their marketing campaigns (Accenture 2002). Hence, there is increasing interest in deploying systematic, analytic processes to generate insights, guide creative thinking for developing more effective marketing programs, and measure outcomes.

Marketing Engineering capitalizes on these trends, which favor both the supply of and demand for marketing analytics. Not only does ME enable marketers to capture the essence of marketing problems in well-specified models, it also improves their ability to make decisions that influence market outcomes. But the mere availability, or use, of marketing analytics does not necessarily affect managerial or organizational performance; rather, analytics must become part of the company's basic managerial decision-making capabilities.

Managers recognize that a model does not provide the complete answer and therefore correctly believe that model results cannot be implemented without modifications by judgments. If model results are tempered by intuitive judgments, why not rely on judgments in the first place? This question reflects a non sequitur—it simply does not follow. As Hogarth (1987, p. 199) notes, "When driving at night with your headlights on you do not necessarily see too well. However, turning your headlights off will not improve the situation."

Decision support tools and mental models must be used in conjunction so that each strengthens the areas in which the other is weak. Mental models can incorporate idiosyncratic aspects of a decision situation, but they may force-fit new cases into old patterns. Decision models may be consistent and unbiased, but they can underweight or ignore idiosyncratic aspects of the situation. Blattberg and Hoch (1990) find that forecasting accuracy improves when managers combine the forecasts generated by decision models with those from mental models; a 50–50 (equal weighting) combination of these two forecasts was best.

In this sense, ME can be both data-driven and knowledge-driven. A data-driven support tool answers "what if" questions on the basis of a quantified market response model. A knowledge-driven decision support tool captures the qualitative knowledge available about a particular domain.

But there are yet other benefits to an ME approach. Managers can explore more decision options, consider decision options more distant from the "base solutions," assess the relative impact of different marketing decision variables more precisely, facilitate group decision making, and enhance their own subjective mental models of market behavior. In essence, the ME approach leads to better and more systematic marketing decision making.

Examples of Marketing Engineering Success

Various well-documented examples have demonstrated that companies can derive substantial benefits from the application of the ME approach to decision making. We outline just a few here.

EXAMPLE

ABB Electric, a manufacturer and distributor of power generation equipment, wanted to increase its sales and market share in an industry that was facing a projected 50% drop in demand. By carefully analyzing and tracking customer preferences and actions, it determined which customers to focus its marketing efforts on and what features of its products were most important to those customers. It credits its ability to go from just 4% to over 40% market share, while raising its profitability in a declining market, to its ME application of *choice models* (Gensch, Aversa, and Moore 1990).

EXAMPLE

The *Marriott Corporation* was running out of good downtown locations for new full-service hotels. To maintain its growth, Marriott's management planned to locate hotels outside the downtown area that would appeal to both business and weekend leisure travelers. The company designed and developed the highly successful Courtyard by Marriott chain using a key ME approach: *conjoint analysis* (Wind et al. 1989).

EXAMPLE

Syntex Laboratories was concerned about the productivity of its sales force. In particular, managers were unsure whether the size of the sales force was right for the job it had to do and whether the firm was allocating its efforts to the most profitable products and market segments. The company used an ME *resource sizing and allocation tool* to develop sales force deployment strategies—and added over $25 million in annual profits over and above its strategic plan (Lodish et al. 1988).

EXAMPLE

The German Railroad Corp. (a $15 billion company) historically priced transportation between any two points as a simple multiple of the distance between them. However, this price structure was not competitive with automobile usage. On the basis of a *large-scale conjoint analysis*, the company launched a "BahnCard" that allows customers to buy tickets at large discounts off the standard per kilometer fares. With the card, many more passengers found the train an attractive alternative to driving. With 3.5 million cardholders, the BahnCard has increased the firm's profits by more than $200 million per year (Dolan and Simon 1996).

EXAMPLE

Rhenania, a medium-sized German direct mail-order company, used a dynamic, multilevel *response modeling system* to answer the most important direct marketing questions: When, how often, and to whom the company should mail its catalogs. This model dynamically evaluates customers on the basis of their past purchase histories and derives the threshold sales per customer needed to maximize profits across time periods and multiple customer segments. The model helped the company increase its customer base by more than 55% and quadrupled its profitability in the first few years after its implementation. The application of the modeling approach also helped propel the company from fifth to second in terms of market position in the German marketplace. In terms of costs, the model paid for itself in a few weeks (Elsner, Krafft, and Huchzermeier 2004).

EXAMPLE

Telering, a leading Austrian cellular phone supplier, was severely threatened by competitive activities. By undertaking a detailed *segmentation study*, Telering identified a new market opportunity, offering no upfront subscription charges, that competitors had trouble mimicking. A sophisticated perceptual mapping study not only made the resulting service innovation credible to senior management and overcame internal barriers to its launch but also provided ideas as to how the product could be introduced through a compelling and relevant advertising campaign.

The new service returned over $20 million in incremental revenue to Telering (Natter et al. 2006).

These examples represent published reports of ME applications that were both technical and organizational successes. But for every such highly visible, large-scale organizational success, thousands of small successes use many of the same ME principles. Imagine—only a few hundred, highly visible professionals make the rounds at golf tournaments, but more than 25 million Americans play the game. Golf professionals serve as exemplars for the golfing public—in much the same way these ME exemplars should inspire marketing professionals in large and small organizations alike.

TOOLS FOR MARKETING ENGINEERING

The wide availability of spreadsheet software, such as Excel, has made it easier to work with mathematical representations of marketing phenomena. For example, marketing spreadsheets typically include planned marketing expenditures and the associated gross and net revenues. However, in most cases, the model developer does not establish a spreadsheet relationship between marketing inputs (e.g., advertising) and sales revenues. Thus, marketing inputs impact net revenue only as cost items. We refer to such spreadsheets as "dumb" models: They make little sense as marketing models because they are silent about the nature of the relationship between marketing inputs and outputs. For the spreadsheet model to make sense, the model developer must define objectives and variables explicitly and specify the relationships between variables. In a "smart" model, the spreadsheet embeds an equation or "response model," which the manager uses to consider the effect of advertising on both sales and revenues and determine if increases or decreases in advertising are justified. Hence, the design environment (knowledge, software, data) facilitates Marketing Engineering.

Market Response Models

Market response models are the basic tools of marketing analytics, the ingredients that can transform a dumb spreadsheet model into a smart one. Response models are critical for systematically addressing many recurring strategic and tactical decision problems in marketing, such as marketing budgeting and mix allocations, customer targeting, and product/company positioning. Without models that describe how customers and markets might respond to marketing actions, it is very difficult to assess the opportunity costs of the decision at hand. And poor response models that lead the decision process astray—just like a golfer who does not stand square to the ball—will likely slice far away from the target.

Market response models require that the following be made explicit:

- *Inputs:* Marketing actions that the marketer can control, such as price, advertising, selling effort, and the like (the so-called marketing mix), as well as noncontrollable variables, such as market size or the competitive environment.
- *Response model:* The link from inputs to measurable outputs of concern to the firm (e.g., customer awareness levels, product perceptions, sales levels, profits).
- *Objectives:* The measure the firm uses to monitor and evaluate actions (e.g., sales in response to a promotion, percentage of a target audience that recalls an ad).

Response models function within the framework of marketing decision models (Exhibit 1.3). A firm's marketing actions (arrow 1), along with the actions of competitors (arrow 2) and environmental conditions (arrow 3), combine to drive the market response, leading to key outputs (arrow 4). Those outputs must be evaluated relative to the objectives of the firm (arrow 5), and the firm then adapts or changes its marketing actions, depending on how well it is doing (arrow 6) — the decision–modeling link.

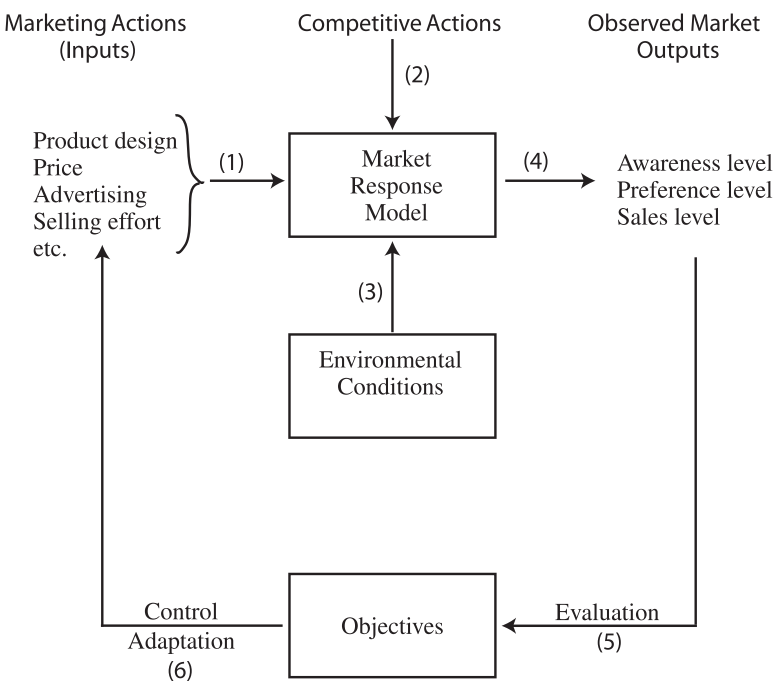


EXHIBIT 1.3
Market response models translate marketing inputs, competitive actions, and environmental variations into observed market outputs within the framework of a marketing decision model.

The ME approach enables managers to be more systematic about how they make decisions in partially structured decision situations. Without ME, firms resort to statements such as the following: "Sales in Minneapolis are down 2.3% relative to forecast [was the goal to meet or exceed the forecast?]; I suggest that we increase our promotional spending there by 10% over the previous plan. [Note the assumption: An increase in current promotional spending (input) will lead to a (short-term?) sales response of at least +2.3% and will be cost effective.]" With ME, this statement instead might appear as follows: "Sales are down 2.3% in Minneapolis. After including that information in our database and recalibrating our Minneapolis response model, it looks as if a promotional spending increase of 12.2% will maximize our profit in that market this quarter."

Types of Response Models

To a craftsperson with a hammer, the entire world looks like a nail, but the availability of a screwdriver introduces a host of opportunities. So it is with marketing models, which can be characterized in several ways:

- *By the number of marketing variables:* Do we consider the relationship between advertising and sales alone (a one-variable model), or do we include price as well (a two-variable model)?
- *By whether they include competition:* Does the model explicitly incorporate the actions and reactions of competitors, or is competition considered simply part of the environment?
- *By the nature of the relationship between input and output variables:* Does every dollar of advertising provide the same effect on sales (a linear response), or are there ranges of spending in which an additional dollar causes larger or smaller returns (an S-shaped response)?
- *By whether the situation is static or dynamic:* Do we want to analyze the flow of actions and market response over time or simply consider a snapshot at one point in time?
- *By whether the models reflect individual or aggregate response:* Do we want to model the responses of individuals (for direct marketing or to target specific sales efforts) or overall response (the sum of individual responses)?
- *By the level of demand analyzed:* To determine the sales of a brand, should we analyze brand sales directly (the most common approach) or consider market share and total market demand, whose product is sales, separately?

In addition to these characteristics, several common terms are important to understand when dealing with market response models.

Parameters are the constants (usually *a*s and *b*s, not *x*s and *y*s) in the mathematical representation of models. To make a model form apply to a specific situation, we must estimate the parameter values, which infuses life into an abstract model. Parameters often have direct marketing referents (e.g., market potential, price elasticity).

Calibration is the process of determining appropriate values for the parameters. To calibrate a model, a marketer might use statistical methods (i.e., estimation), some sort of judgmental process, or a combination of approaches. For example, a simple model is:

$$\text{SALES} = \text{a} + \text{b} \times \text{ADVERTISING}$$

In this equation, *ADVERTISING* is an **independent variable**, *SALES* is a **dependent variable**, the model form is **linear**, and *a* and *b* are **parameters**. Note that *a* is the level of *SALES* when *ADVERTISING* equals 0, or the base sales level. For every dollar increase in advertising, the equation says that we should expect a change in sales of *b* units. Here, *b* is the slope of the sales/advertising response model. If we can determine that the proper values of *a* and *b* are 23,000 and 4, respectively, we place those values in the equation to get:

$$\text{SALES} = 23{,}000 + 4 \times \text{ADVERTISING}$$

so we may say we have calibrated the model (i.e., given values to its parameters).

But how do we perform this calibration, that is, select "good" parameters? We want estimates of *a* and *b* that make the relationship $SALES = a + b \times ADVERTISING$ a good approximation of how *SALES* varies with the values of *ADVERTISING*, which we may attain from data or intuition.

People often use least squares regression to calibrate a model. In effect, if we have several observations of *ADVERTISING*, the **X-values** (call them x_1, x_2, etc.), and the associated observations of *SALES*, the **Y-values** (called y_1, y_2, etc.), the regression estimates of *a* and *b* are those values that minimize the sum of the squared differences between each of the observed *Y* values and the associated "estimate" provided by the model. For example, $a+bx_7$ would be our estimate of y_7, and we want y_7 and $a + bx_7$ to be close. We may have actual data about these pairs of *X*s and *Y*s, or we may have to use our best judgment to generate them ("What level of sales would we get if our advertising was 10 times what it is now? What if it was half of what it is now?").

When the data that we use for calibration are actual experimental or market data, we call the calibration task "objective calibration" (or objective parameter estimation). In many cases, managers do not have relevant historical data for calibrating the model. If the firm always spends about the same amount for advertising (say, 4% of sales in all market areas), it has no objective information about what would happen if it changed the advertising-to-sales ratio to 8%. Alternatively, the firm may have some historical data that are no longer relevant because of changes in the marketplace, such as new competitive entries, changes in brand price structures, varying customer preferences, and the like. (Imagine using year-old data in the cellular devices market to predict future market behavior!)

For subjective calibrations, we must rely on judgment calls. For example, a judgmental calibration mechanism might consist of the following questions:

Q1: What is our current level of advertising and sales?
(A: advertising = \$8/capita; sales = 25 units/capita)

Q2: What would sales be if we spent \$0 in advertising?
(A = \$0/capita)

Q3: What would sales be if we cut 50% from our current advertising budget?
(A = \$4/capita)

Q4: What would sales be if we increased our advertising budget by 50%?
(A = \$12/capita)

Q5: What would sales be if advertising were made arbitrarily large?
(A = \$XXX/capita)

Whether using an objective or subjective calibration, we need an idea of how well the model represents the data. One frequently used index is R^2, or R-square. If each of the estimated values of Y equals the actual value of Y, then R-square has a maximum value of 1; if the estimates of Y only perform as well as the average of the Y values, then R-square has a value of 0. If R-square is less than 0, the model performs worse than if we simply assigned the average value of Y to every value of X. In that case, we have a very poor model indeed.

The equation or relationship between advertising and sales that we discussed above is one every marketer knows—it is a straight line. But we are not limited to straight-line relationships for response models; there are many types that are in common use and more appropriate than straight lines for certain marketing situations. (See the Technical Notes at www.mktgeng.com for details on all the issues we discuss here.)

Dynamic Effects

Responses to marketing actions rarely take place instantly. For example, the effect of an ad campaign does not end when that campaign is over; part of it will continue in a diminished way for some time. Similarly, many customers purchase more than they can consume of a product during a short-term price promotion, which causes an inventory buildup in their homes and therefore lowers sales in subsequent periods. Furthermore, the effect of a sales promotion depends on how much inventory buildup has occurred in prior periods (i.e., how much potential buildup is left). If customers stocked up on Brand A cola last week, a new promotion this week probably will be less effective than one several weeks in the future.

Carryover effects refer to the influence of a current marketing expenditure on sales in future periods. There are several types of carryover effects. The **delayed-response effect** arises from delays between when marketing dollars are spent and their impact. Delayed response is especially evident in industrial markets, in which the delay, especially for capital equipment, can be a year or more. Another type of effect, the **customer-holdover effect**, arises when new customers created by marketing expenditures remain customers for many subsequent periods, so their later purchases should be credited to some extent to the earlier marketing expenditures. Some percentage of these new customers will be retained in each subsequent period; this phenomenon gives rise to the notion of the **customer retention rate** and its converse, the **customer decay rate** (also called the attrition or erosion rate). **New trier effects**, in which sales reach a peak before settling down to a steady state, are common for frequently purchased products, for which many customers try a new brand but few become regular users. **Stocking effects** occur when a sales promotion not only attracts new customers but also encourages existing customers to stock up or buy ahead. The stocking effect often leads to a sales drop in the period following the promotion.

Market Share and Competition

Marketing engineering models can be built at many levels. Managers use models of brand sales, models of the total market, and models of market share, among others. These three types of models have an intimate and important relationship, by definition:

$$\text{Brand Sales} = \text{Market Sales} \times \text{Market Share}$$

This equation is a powerful reminder that marketers obtain (brand) sales by extracting market share from the market in which they operate. Thus, a firm's action may influence sales by affecting the size of the market, share of the market, or both. Thus, a marketing action might result in zero incremental sales for at least two reasons. First, it might have no effect at all. Second, it might provoke a competitive response, which increases total product class sales but lowers the firm's share in that market. The preceding equation helps disentangle such effects.

Models of market or product class sales have several common functional forms and can use forecasting methods or demand build-up procedures that rely on environmental variables (e.g., population size, growth, prior sales levels). Market share models are a different story. To be logically consistent, regardless of what any competitor does in the marketplace, each firm's market share must be between 0 and 100% (range restriction), and market shares summed over brands must equal 100% (sum restriction).

A class of models that satisfies both the range and the sum restrictions are **attraction models**, which determine the attraction of a brand on the basis of its marketing mix. Essentially, these models say:

$$\text{Share} = \frac{\text{Attractiveness of Offering}}{(\text{Attractiveness of Offering} + \text{Attractiveness of Competitive Offerings})}$$

where attractiveness is measured from the perspective of potential customers.

Response at the Individual Customer Level

Thus far, we have looked at aggregate market response at the level of the entire marketplace. However, markets are composed of individuals, so we can analyze the response behaviors of those individuals and either use them directly (at the segment or segment-of-one level) or aggregate them to form total market response. In Chapter 2, we describe how individuals and groups of individuals can be modeled in a Marketing Engineering framework.

Objectives

To evaluate marketing actions and improve the performance of the firm in the marketplace, managers must specify objectives. (See Exhibit 1.3.) Those objectives may have different components (profit, market share, sales goals) but must specify the time horizon, deal with future uncertainty, and address the issue of which objectives to pursue.

Short-run profit

The simplest and most common objective is to maximize short-run profit. The equation focusing on that single marketing element in a static environment is:

$$\begin{aligned}\text{Profit} &= (\text{Unit price} - \text{Unit variable cost}) \times \text{Sales} \\ &\quad\ \text{volume} - \text{Relevant costs} \\ &= \text{Unit margin} \times \text{Quantity} - \text{Costs}\end{aligned}$$

Response models characterize how the sales volume is affected by marketing actions. If our focus is on price, then (assuming costs are fixed) as price increases, the unit margin goes up and sales generally go down. If we focus on another marketing instrument, such as advertising, the margin is fixed and quantity goes up, but costs go up as well.

Relevant costs generally consist of two components: fixed and discretionary. **Discretionary costs** are those associated with the marketing activity under study and should always be considered. **Fixed costs** include plant and overhead expenditures that should be allocated appropriately to marketing activity. Allocating fixed costs is thorny and difficult; it keeps accountants employed and frequently frustrates managers of profit centers.

For our purposes, only two questions are relevant regarding fixed costs:

- *Are the fixed costs really fixed?* Suppose that tripling advertising spending leads to a 50% sales increase, leading in turn to the need to increase plant size. Capacity expansion costs then must be taken into account. Normally fixed costs are locally fixed; that is, they are fixed within the limits of certain levels of demand and shift to different levels outside those regions. As with our response models, as long as we focus our attention to a limited range of independent variables, most fixed costs are indeed fixed.
- *Are profits greater than fixed costs?* If the allocated fixed costs are high enough, absolute profitability may be negative. In this case, the decision maker may want to consider dropping the product, not entering the market, or some other action.

Long-run profit

If a marketing action or set of actions causes sales that are realized over time, we may want to consider profit over a longer time horizon. If we look at the profit stream over time, an appropriate way to deal with long-run profits is to take the present value (PV) of that profit stream:

$$PV = Z_0 + Z_1 r + Z_2 r^2 + Z_3 r^3 \ldots,$$

where Z_1 is the profit for period i, and $r = 1/(1 + d)$, with d being the discount rate (typically 20% or more per year, depending on the firm and the nature of the marketing investment). The discount rate d is often a critical variable; the closer d is to 0, the more oriented toward the long term the firm is, whereas a high value of d (over .25 or so) reflects a focus on more immediate returns. In practice, the more certain the earnings flow, the lower is the discount rate that firms use.

Multiple goals and multiple decision makers

Although profit of some sort is an overriding goal of many organizations, it is not the only factor managers consider in trying to decide among possible courses of action. Managers may say, “We want to maximize our market share and our profitability in this market!” or “We want to bring out the best product in the shortest possible time.” Such statements are attractive rhetoric but show faulty logic. For example, firms can almost always increase market share by lowering the price; after some point however, profits decrease while market share continues to increase. And when prices become lower than costs, profit becomes negative even though market share is still increasing!

If a firm has two or more objectives that conflict, how can the decision maker weigh those goals to rank them unambiguously? The simplest and most common approach is to choose one (the most important) objective—say, profit—and make all the others constraints (e.g., market share must be at least 14%). However, whether companies use a simple formal method, such as a single goal plus constraints, or a more sophisticated method to measure the trade-offs among goals, it is critical that they neither ignore nor poorly assess important goals.

Various stakeholders in an organization may not agree about the goals. Marketers typically are more concerned about market share and sales growth than are financial analysts; time horizons also vary according to those involved in the decision. Therefore, it is important that some level of understanding about (if not agreement on) stakeholder differences in goals be incorporated into the decision-making process. (See Chapter 2.)

After the firm has specified its goals or objectives, the ME approach facilitates the process of decision making by suggesting the values of the independent variables (e.g., advertising, selling effort, promotional spending) that will offer the best opportunity to achieve these goals.

Shared Experience and Qualitative Models

Our preceding discussion focuses on quantitative response models—equations that develop a formal analytic structure of the marketplace. We now introduce two other forms of modeling that have proved valuable: shared experience and qualitative models.

Shared experience models

If we lack data about the way a market responds, it may be valuable to pool the experience of a wide range of businesses and develop norms or guidelines for response behavior from these pooled data. There are many ways that such pooling takes place, including benchmarking (comparing operations against acknowledged good alternatives), which facilitates systematic comparisons with an exemplar or strong outside comparison point.

Qualitative response models

Some decision situations call for qualitative insights (e.g., new copy for an advertising campaign, structuring a negotiation between a buyer and a seller from different cultures). The experience attained by knowledgeable practitioners and the guidelines generated by academic research can be useful in these situations. Qualitative response models help represent qualitative knowledge and insights.

If a particular phenomenon can be described best in a qualitative fashion, a precise numerical model may be inappropriate for representing what is known. For example, if we can characterize consumer response to an ad only as positive, neutral, or negative, a precise numerical model is inappropriate.

EXAMPLE

The possible responses to a price reduction by a competitor might be (1) match the new price, (2) maintain the current price, (3) change TV advertising, (4) increase trade promotion, or (5) fire the brand manager. These options do not fall along an easily characterized continuum.

EXAMPLE

A retailer might react to a trade promotion by always accepting the deal, but what it does with that promotion may depend on coop (shared) advertising dollars. If the deal includes coop money, the retailer accepts the deal and passes on all of the discount to the consumer. If the discount is greater than 30%, it puts up a big display. Otherwise, the retailer leaves the item at its regular price and does not use an ad feature or a display.

We can use qualitative response functions in decision models by adopting nonmathematical representation schemes. Perhaps the most widely used approach is a rule-based representation, which states the response model in the form of rules, or statements joined by the connectives AND, OR, and NOT, and properly specified by the qualifiers FOR ALL and THERE EXISTS. Using this representation, the retailer example becomes a set of rules in computer representation form:

If the deal includes coop money,
  Then the retailer will accept the deal.

If the deal includes coop money,
  Then the retailer will pass on all the discount to the consumer.

If the deal discount is greater than 30%,
  Then the retailer will put up a big display.

If NOT (the deal includes coop money) AND NOT (discount is greater than 30%),
  Then the retailer will sell the item at regular price.

If NOT (the deal includes coop money) AND NOT (discount is greater than 30%),
  Then retailer will use ad feature = No.

If NOT (the deal includes coop money) AND NOT (discount is greater than 30%),
  Then retailer will use display = No.

When a response model consists of a set of rules, artificial intelligence techniques, particularly logical inference, can derive recommendations in specific decision situations. Such rule sets also can help develop knowledge-based systems to support marketing decisions.

Choosing, Evaluating, and Benefiting from a Marketing Engineering Model

Response models are approximations of likely market or customer behavior and thus may vary, sometimes substantially, from the unknown, true response behavior. In some sense, all models are wrong, but many are useful. Model users must choose among those that are useful and those that are not. One model form is not better than another; rather, each is useful in some situations and for some purposes. Although various criteria dictate which model to select, here are four that apply specifically to response models.

Model specification

- Does the model include the right variables to represent the decision situation?
- Are the variables, as represented, managerially actionable?
- Does the model incorporate the expected behavior of individual variables?
- Does the model incorporate the expected relationships between variables?

Model calibration

- Can the model be calibrated using data from managerial judgments or historical data?
- Can the model be calibrated through experimentation?

Model validity and value

- Does the level of detail in the model match that in the available data?
- Does the model reproduce the current market environment reasonably accurately?
- Does the model provide value-in-use to the user?
- Does the model represent the phenomenon of interest accurately and completely?

Model usability

- Is the model easy to use? (Is it simple, does it convey results in an understandable manner, and does it permit users to control its operation?)
- Is the model, as implemented, easy to understand?
- Does the model give managers guidance that makes sense?

When we select a model, we can summarize these criteria into one overriding question: “Does this model make sense for this situation?" That is, does the model have the right form, can it be calibrated, is it valid, and is it useful? If the answers to these questions are all *yes*, then the model is appropriate.

BUSINESS VALUE OF MARKETING ENGINEERING: FROM PROMISE TO REALITY

Marketing Engineering succeeds because of sophisticated managers, not because of sophisticated models. Such managers recognize that decisions affect many stakeholders and that most people resist change and will not embrace decision processes they do not understand or decisions unfavorable to their interests. Therefore, developing good decisions is only half the battle. It is just as important to make those decisions acceptable to stakeholders within a firm; in many situations, model users and decision makers are different people. Models also help people understand and accept decisions by improving communications among the stakeholders.

By clearly stating model assumptions and explaining the results, managers can replace positions with principles. Instead of saying "Let's do X," a manager might say, "I believe that our objective should be A, and according to the model, X is a good way to achieve that objective." If the process of articulating model assumptions is well orchestrated, the ensuing discussion will focus on the merits of those assumptions rather than the appropriateness or validity of the model output. Models are particularly useful when they help change mental models by challenging the assumptions or beliefs that underlie those mental models. A model also provides an explicit mechanism for including stakeholders in the decision process. At Syntex Labs, discussed previously, stakeholders participated by providing inputs to the model and helping implement model results. Interested parties are more likely to accept decisions resulting from a model if they know their inputs and judgments are part of the process. In Chapter 8, we pull together a few critical lessons on the successful implementation of ME.

STRUCTURE OF THIS BOOK

For the reader who wants a broad perspective on ME, this book is designed to be read like any other. For the reader who wants to gain deep understanding and experience with ME, we provide substantial additional material on our Web site, www.mktgeng.com, including software, software tutorials, and technical appendices that provide more details about the models described herein. Although readers can work directly with the ME models using our software, we have not written this book for marketing analysts or modelers. Rather, our main goal is to help you become an astute user of well-established models and a knowledgeable consumer of the modeling results generated by others.

In particular, we hope this book will enable you to recognize decision situations that could benefit from an ME approach and help you focus your modeling efforts and your interpretation of results to facilitate the decision-making process. Specifically, we attempt to provide a basic understanding of the most successful marketing decision models, offer examples that show why they are successful, and give you some real experience with ME. In general, it is best to get the basic ideas from the text, refine that understanding through the use of the cases and software, and then use the technical notes mainly as backup.

We chose the models in this book to be both theoretically sound and practically useful, as the cases, exercises, and software on our Web site demonstrate. The models we describe here are all widely used in industry, which means they are robust and have been tested in field settings.

Chapter 2 deals with understanding customers and customer groups. We discuss how customers gather information, form preferences, and make decisions, both individually and in groups (i.e., organizational buying situations). Understanding both functional and psychological needs is critical. Such an understanding provides the basis for creating ME models that describe what customers value and how they might respond to marketing actions.

In Chapter 3, we focus on ME approaches that address a core strategic marketing issue: Which customer segments should we choose to serve? To answer this question effectively, marketers need tools to understand how a market is segmented and determine which segments are most attractive.

Chapter 4 deals with another core strategic marketing issue: How should we position our offerings in competitive markets, so that they are perceived as superior by those customers and segments we choose to serve? Again, ME approaches provide insight into this question that helps marketers avoid inefficient allocations of their limited resources.

Chapter 5 deals with methods of forecasting, for both new and established products. We cover both judgment-based and data-based approaches and show why combining the two is often a very effective strategy.

In Chapter 6, we describe concepts and tools for marketing new products or, more generally, new offerings. Therefore, we focus heavily on methods that support the design of new products and conjoint analysis in particular.

Chapter 7 addresses marketing budgeting and resource allocation decisions—how much to spend and where (what marketing mix elements, what programs, what channels?) and when to spend it.

Finally, Chapter 8 discusses what we know about the implementation of ME in an organizational context, focusing on the elements necessary for success, as well as those that can lead to failure. It then considers the future of ME.

SUMMARY

In this chapter, our primary objective is to introduce the field of Marketing Engineering—the use of interactive computer decision models to facilitate marketing decisions. More and more marketing managers are functioning in decision environments characterized by increasing amounts of data, information (summarized data), and computing resources. Such managers need various concepts and tools to survive and thrive in such environments.

The ME approach is centered around interactive decision models, which are customizable, computerized representations of marketing phenomena that enhance managerial decision making. We provide a basic overview of the types of models and how they are constructed. We also describe some of the many potential benefits of using decision models, including improving decision consistency, gaining an ability to evaluate more decision options, assessing the relative impact of different factors on a decision, and updating mental models of market behavior. Finally, we summarize several reasons many managers cite for choosing not to use decision models, despite their potential benefits, with the hope that this book and related material can deflect those concerns.