

6

Customer Analysis

OVERVIEW

Without customers, a business cannot survive. Although this may seem obvious, and despite the widespread adoption of the “marketing concept,” many managers have regretted not obtaining sufficient information about their customers to develop products or strategies that meet customer needs. For example, despite spending millions of dollars on marketing research, automobile manufacturers missed the female market for years because they failed to adapt products and the sales environment to the fact that women were both influencing and making more automobile purchases.

In this chapter the term *customer* refers not only to current customers of a given product but also to both customers of competitors and current noncustomers of the product category (i.e., potential customers). It also refers to both immediate customers¹ (i.e., supermarkets and discount stores for consumer product companies such as P&G and manufacturers for component manufacturers such as Intel) and final customers (i.e., individuals and businesses).

Each customer is unique to some degree. As a consequence, mass marketing (one marketing program for all customers) is typically inefficient. Since it is time consuming and not very profitable to develop a separate strategy for each customer, some grouping of customers into segments is often useful.² Segmentation is a compromise between treating each customer as unique and assuming all customers are equal. Segmentation programs provide insights about different kinds of customer behavior and make mar-

¹Customers, of course, include channel members. While we focus on end customers for the product or service, most of the analyses discussed apply equally to channel members.

²Some categories have so few customers that each can be treated as a separate segment and analyzed separately. Examples are passenger aircraft, military products (e.g., battle tanks), and nuclear generators. In addition, there is a trend toward *mass customization*, or one-to-one marketing, which focuses on marketing products and services to individuals rather than to segments. Examples are Levis custom-tailored jeans for women and Internet-based services that the user can customize (Pine, Victor, and Boynton, 1993).

FIGURE 6-1 What We Need to Know about Current and Potential Customers

Who buys and uses the product
 What customers buy and how they use it
 Where customers buy
 When customers buy
 How customers choose
 Why they prefer a product
 How they respond to marketing programs
 Will they buy it (again)?

keting programs more efficient. Of course the ultimate segmentation is at the individual level. As information technology has advanced, (as small retail operators have always known) so-called one-to-one marketing has become a more viable approach, but, segmentation is still the norm.

In this chapter, we do three things. First, we suggest an approach to systematically analyzing customers. Figure 6-1 shows the main parts of this analysis. Product managers need to answer eight questions. Who are the customers for this product or service? What are customers buying and how do they use it? (Customers buy benefits rather than simply product features or characteristics.) Where do customers buy products? When are purchase decisions made? How do customers make purchase decisions? Why do customers choose a particular product? In other words, how do they value one option over another? How do they respond to marketing programs such as advertising and promotions? And finally, will they buy it again? Second, we introduce the concept of long-term value of a customer. Finally, we discuss market segmentation. Both general criteria and specific analytical methods are presented.

What We Need to Know about Customers

Who Buys and Uses the Products

Buyers versus Users. For most industrial goods and many consumer products, the *who* must be broken into several different entities within the organization or household, including the following:

1. Initiator (who identifies the need for product).
2. Influencer (who has informational or preference input to the decision).
3. Decider (who makes the final decision through budget authorization).
4. Purchaser (who makes the actual purchase).
5. User.

The identities of the above customers can differ widely, particularly the user and the buyer. For example, in an industrial market, the end user may be an engineer who is concerned mainly with technical features, whereas the purchasing agent emphasizes cost and reliability of delivery. One reason for the success of Federal Express was its ability to take the decision on how to send overnight packages away from the shipping clerk by

FIGURE 6-2 Buying Roles and Needs/Benefits Sought

Needs/Benefits Sought	Buying Roles				
	Initiator(s)	Influencer(s)	Decider(s)	Purchaser(s)	User(s)
A					
B					
C					
D					

making the user the purchaser. Similarly, adults often purchase cereal, toys, or fast-food meals even though the user of the product is a child. McDonald's ads clearly recognize this and attempt to target both teenagers (who have money of their own) and the family meal segment, in which the child is likely to influence where the family goes to eat. Products targeted toward gift givers (e.g., silverware as a wedding gift) also highlight the difference between the buyer and the user.

This distinction among buyer, user, and other purchase influencers is particularly important for industrial products. The mark of a top salesperson is the ability to identify the different people involved in making a decision, understand the relative power over the purchase each person holds, and learn what they value. For example, in selling word processing software to a law firm, the needs of the secretaries (ease of use, mouse support, readable screen) differ from those of the office manager (high productivity, no bugs in the software, good service) and from the person approving the purchase (low cost, reliable delivery). Figure 6-2 provides a template for this kind of analysis.

Descriptive Variables: Consumer Products. The most obvious and popular basis for describing consumers is their general characteristics (Figure 6-3). The key categories are:

1. **Demographic.** The most commonly used demographics are age, sex, geographic location, and stage in the family life cycle. These characteristics have the advantage of being relatively easy to ascertain. Unfortunately in many cases, segments based on demographics are not clearly differentiated in their behavior toward the product.
2. **Socioeconomic.** Socioeconomic variables include income and such related variables as education, occupation, and social class, with income and education generally being more useful. As in the case of demographics, the relationship between these variables and purchase behavior can be weak.
3. **Personality.** Given the relatively limited predictive power of demographic and socioeconomic variables, the fact that many marketing people are trained in psychology, and the natural desire to find a general basis for dividing up consumers that will be useful across many situations, it is not surprising that marketers have attempted to use personality traits as a basis for segmentation. Unfortunately,

FIGURE 6-3 Major Segmentation Variables for Consumer Markets

Variable	Typical Breakdown
Geographic	
Region	Pacific, Mountain, West North Central, West South Central, East North Central, East South Central, South Atlantic, Middle Atlantic, New England
City or metro size	Under 5,000; 5,000–20,000; 20,000–50,000; 50,000–100,000; 100,000–250,000; 250,000–500,000; 500,000–1,000,000; 1,000,000–4,000,000; 4,000,000 or over
Density	Urban, suburban, rural
Climate	Northern, southern
Demographic	
Age	Under 6, 6–11, 12–19, 20–34, 35–49, 50–64, 65+
Gender	Male, female
Family size	1–2, 3–4, 5+
Family life cycle	Young, single; young, married, no children; young, married, youngest child under 6; young, married, youngest child 6 or over; older, married, with children; older, married, no children under 18; older, single; other
Income	Under \$10,000; \$10,000–\$15,000; \$15,000–\$20,000; \$20,000–\$30,000; \$30,000–\$50,000; \$50,000–\$100,000; \$100,000 and over
Occupation	Professional and technical; managers, officials, and proprietors; clerical, sales; craftspeople, foremen; operatives; farmers; retired; students; homemakers; unemployed
Education	Grade school or less; some high school; high school graduate; some college; college graduate
Religion	Catholic, Protestant, Jewish, Muslim, Hindu, other
Race	White, black, Asian
Nationality	American, British, French, German, Italian, Japanese
Psychographic	
Social class	Lower lowers, upper lowers, working class, middle class, upper middles, lower uppers, upper uppers
Lifestyle	Straights, swingers, longhairs
Personality	Compulsive, gregarious, authoritarian, ambitious
Behavioral	
Occasions	Regular occasion, special occasion
Benefits	Quality, service, economy, speed
User status	Nonuser, ex-user, potential user, first-time user, regular user
Usage rate	Light user, medium user, heavy user
Loyalty status	None, medium, strong, absolute
Readiness stage	Unaware, aware, informed, interested, desirous, intending to buy
Attitude toward product	Enthusiastic, positive, indifferent, negative, hostile

Source: Philip Kotler, *Marketing Management*, 8th Ed., 1994, p. 271. Adapted with permission of Prentice-Hall, Inc. Upper Saddle, NJ.

personality variables have proven even less useful than demographic or socioeconomic variables in predicting purchasing behavior.

4. **Psychographics and values.** Psychographics basically represent an evolution from general personality variables to attitudes and behaviors more closely related to consumption of goods and services. Also known as lifestyle variables, psychographics generally fall into three categories: activities (cooking, sports, traveling,

FIGURE 6-4 Lifestyle Typologies

<i>Vals</i>	<i>Vals2</i>	<i>Globalscan</i>
Inner-directed consumers	Principle-oriented consumers	Strivers
Societally conscious	Fulfilleds	
Experientials	Believers	Achievers
I-am-me consumers		
Outer-directed consumers	Status-oriented consumers	Pressured
Achievers	Achievers	
Emulators	Strivers	Adapters
Belongers		
Need-driven consumers	Action-oriented consumers	Traditionals
Sustainers	Experiencers	
Survivors	Makers	
	Strugglers	

etc.), interests (e.g., art, music), and opinions. They are thus, not surprisingly, often referred to as AIO variables. These have been widely used as bases for segmentation and for the creation of advertising themes. Many researchers have used the VALS (Values and Lifestyles) typology and its updated version, VALS2, (see Figure 6-4) developed by SRI International as a basis for defining segments.³ Figure 6-4 also shows a lifestyle typology, GLOBALSCAN, which was developed by the advertising agency Backer Spielvogel Bates Worldwide. GLOBALSCAN was based on a survey of 15,000 adults in 14 countries.

Another typology, the List of Values (LOV) Scale (Kahle, Beatty, and Homer, 1986), delineates nine basic values:

1. Self-respect.
2. Security.
3. Warm relationship with others.
4. Sense of accomplishment.
5. Self-fulfillment.
6. Sense of belonging.
7. Respect from others.
8. Fun and enjoyment.
9. Excitement.

These typologies are often related to purchasing patterns and afford the product manager the opportunity to match potential buyers with the appropriate media and message to communicate with them (Corfman, Lehmann, and Narayanan, 1991).

³Readers interested in categorizing themselves on the VALS2 scale can do this through the World Wide Web site <http://future.sri.com/vals/survey.html>.

FIGURE 6-5 Major Segmentation Variables for Business Markets

Demographic

- *Industry*: Which industries should we focus on?
- *Company size*: What size companies should we focus on?
- *Location*: What geographical areas should we focus on?

Operating Variables

- *Technology*: What customer technologies should we focus on?
- *User/nonuser status*: Should we focus on heavy, medium, light users or nonusers?
- *Customer capabilities*: Should we focus on customers needing many or few services?

Purchasing Approaches

- *Purchasing-function organization*: Should we focus on companies with highly centralized or decentralized purchasing organizations?
- *Power structure*: Should we focus on companies that are engineering dominated, financially dominated, etc.?
- *Nature of existing relationships*: Should we focus on companies with which we have strong relationships or simply go after the most desirable companies?
- *General purchase policies*: Should we focus on companies that prefer leasing? Service contracts? Systems purchases? Sealed bidding?
- *Purchasing criteria*: Should we focus on companies that are seeking quality? Service? Price?

Situational Factors

- *Urgency*: Should we focus on companies that need quick and sudden delivery or service?
- *Specific application*: Should we focus on certain applications of our product rather than all applications?
- *Size of order*: Should we focus on large or small orders?

Personal Characteristics

- *Buyer-seller similarity*: Should we focus on companies whose people and values are similar to ours?
- *Attitudes toward risk*: Should we focus on risk-taking or risk avoiding customers?
- *Loyalty*: Should we focus on companies that show high loyalty to their suppliers?

Source: Philip Kotler, *Marketing Management*, 8th Ed., 1994, p. 278. Adapted by permission of Prentice-Hall, Inc. Upper Saddle River, New Jersey.

Descriptive Variables: Industrial Products. The same type of variables used to describe consumers can also be used to describe organizations (see Figure 6-5 for a list of some of the most popular variables used). For industrial product customers, the traditional focus has been on firm characteristics such as size of the company, industry, and location; that is, the demographic variables appropriate for describing companies. However, a variety of other kinds of variables can be used, such as operating variables (e.g., customer technology), purchasing approaches (e.g., centralized versus decentralized purchasing operations), situational factors (e.g., order size), and "personal" characteristics (e.g., attitude toward risk).

Concepts of personality and psychographics can also be applied in the context of organizations. Although it may be unusual to think of a firm as having a personality, one important segmentation variable in technologically oriented industries is innovativeness. The innovators, organizations that adopt new technologies earlier than others in their industry, are often referred to as "lead users." Lead users have two characteristics:

(1) They face general needs months or years before the bulk of the industry does, and (2) they can benefit significantly by obtaining an early solution to those needs (Urban and von Hippel, 1988). These are obviously valuable customers, as they not only provide early sales and spread (hopefully) favorable word of mouth information, but also help the company make necessary product modifications and improvements.

Many of the same variables used to segment markets for consumer and industrial goods are used to segment markets internationally. Figure 6-6 lists key segmentation variables used in direct marketing campaigns in Europe.

What Customers Buy and How They Use It

The most obvious answer to the “what” question revolves around the identity of the items or services purchased (including market shares, purchase amounts, and features chosen). Any product manager who doesn’t have such basic data is generally not long employed.

Benefits. Though many product managers do not seem to realize it, customers do not purchase products and services for the features of the product; rather, customers purchase the *benefits* the product provides. In other words, the firm produces features but customers purchase benefits. Recognizing this distinction is a particular problem in technology-driven companies that tend to focus on the development of new technologies and fancy products without adequate concern about whether the benefits the technology provides solve the customers’ problems better than the old products do.

Focusing on benefits is also important in understanding the competitive set. The old story about the drill manufacturer that recognized it was selling holes, not drills, not only indicates that benefits are more important than the physical product but also helps to define the competition based on the benefit (referred to in Chapter 3 as *generic competition*).

Thus, a key problem facing the product manager is to understand what benefits different customer groups or market segments are seeking. As Figure 6-2 shows, the needs or benefits sought can vary with the buying role in the decision-making unit (as well as by customer segment).

For example, consider a Cadillac Seville. The following distinction can be drawn between features and benefits:

Feature	Benefit
300-horsepower engine	The ability to pull away quickly from potentially dangerous situations. With the increased traffic, you'll feel much safer in this car.
Northstar engine	Engine will not need a tuneup for the first 100,000 miles. You'll enjoy a smooth-running engine with fewer trips to the dealer for service.
Adjustable seats	Controls allow you to make easy adjustments to your seating position so you'll stay fit, alert, and comfortable throughout your trip.
ABS brakes	Even if you step hard on these brakes, your wheels won't lock up and skid. This means you'll have an extra margin of safety.

FIGURE 6-6 Key Segmentation Variables Used in Direct Marketing Campaigns in Europe

	Belgium	Denmark	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain	UK
Most commonly used consumer segmentation criteria	Social class Nielsen zones Geographic Database	Demographic from census Database	Sociodemographic Database	Age Profession Income Family status Lifestyle	Urban/rural Profession Database	Age Income Profession Family status Database	Age Sex Profession Housing types Database	Age Sex Geographic Lifestyle Database	Income Urban/rural Education Political bias Database	Age Sex Education Urban/rural Geographic proximity Database	Age Sex Profession Lifestyle Database
Most commonly used business segmentation criteria	SIC* Size VAT	SIC Size Turnover Decision	SIC Size Turnover	SIC Turnover Size	Size Turnover SIC	Size Turnover Location Liquidity	SIC Size Turnover Number of telephone lines	Size/SIC Turnover Branches Credit rating Decision makers	Size SIC Turnover	Size Turnover	SIC Size

*SIC: Standard Industrial Classification.
Source: Marketing Director International, 1991.

This kind of description, which can be used in a print ad or as part of a sales pitch, appeals both to the features-hungry customer and to the customer who needs the features translated into terms he or she can understand.

As mentioned in Chapter 1, one key trend is the increased use of customer databases for target marketing and customer retention programs. Database marketers often use three criteria for evaluating and segmenting customers in their databases:

1. *Recency*: How recently has the customer bought from you?
2. *Frequency*: How many different products does the customer buy, and what are the time intervals?
3. *Monetary value*: What is the value of the customer's purchases in terms of profits?

The RFM approach is used to rate each customer in the database on a scale, perhaps by multiplying the three criteria and then rank ordering customers in terms of attractiveness. When prospecting for new customers, top-ranked customers can be profiled using the descriptors noted earlier, and then potential customers can be matched against these descriptors.

Product Assortment. Another useful piece of information related to the "what" question involves the number of different brands purchased by customers in the segments. For many frequently purchased consumer goods, panel or similar data are available that provide purchase histories for individual consumers (e.g., brands purchased were A, A, A, B, A, A, C, A, A, A), which when aggregated produces switching tables such as Figure 3-10. For industrial products, it is useful to understand how many different vendors a customer employs and the assortment of models, quality levels, and the like from which the customer chooses. For example, a new plastic may be useful for replacing zinc, aluminum, brass, and so on. For Federal Express, segments might consist of customers of Emery, DHL, UPS, the U.S. Postal Service, fax, and e-mail.

Product Use. Arm & Hammer found out about putting a box in the refrigerator and using baking soda to deodorize drains from customer suggestions. Often customers find uses for a product that the company never dreamed of. Interestingly, the way a product is used may or may not be related to why customers originally bought it.

In addition, defining the exact situation in which the product or service is used is crucial to understanding customers. This includes both where they use it (e.g., at home or in the office) and on what occasions (e.g., for entertaining or everyday use).

Where Customers Buy

Where customers make purchase decisions is a critical input into decisions about the channels of distribution (see Chapter 13). Many product managers think of channels as being fixed and traditional, but customers migrate to other channels as their information needs and other market conditions change.

Take, for example, the home stereo market. During the 1960s, consumers started replacing consoles (the turntable, tuner, and amplifier housed in what looks like a piece of furniture) with stereo components. The locus of purchase was mainly small stereo

stores and some mail-order firms. In the 1990s most of these purchases occurred in electronics superstores such as Circuit City. Recently the Internet has emerged as an important source.

Why did this happen? Several important changes occurred. First, consumers' need for information diminished over time. The component system is no longer a novelty; most people today are not buying their first system but upgrading an old one. Media such as *Consumer Reports* provide excellent information on features and quality. Thus, whereas customers relied on salespeople for technical information and product comparisons in the 1960s, the Circuit City salesperson merely indicates what is on sale and whether it is in stock. In addition, more products are available, which has brought down margins. Large-volume retailers typically dominate in such an environment.

A similar picture emerged in personal computers. The small computer retailers gave way to large hardware and software superstores such as CompUSA, specialized software discounters such as Egghead, mail-order firms such as Dell and Gateway 2000, and eventually Internet sites.

Therefore, tracking where customers are making purchases is very important. The phenomenon of moving from specialty retailer to discounter is often repeated and predictable.

When Customers Buy

A relevant dimension to understanding customers is the timing issue. When they buy encompasses time of year, time of month, and even time of day. Fast-food operators, for example, are known to segment by "daypart," that is, breakfast, lunch, dinner, and snacking times. *When* also includes when customers buy in terms of sales or price breaks and rebates, on the assumption that those who buy because of a special deal (i.e., deal-prone consumers) may be different than those who pay full price.

Some sales variation is predictable due to the nature of the product. Snowblower sales to end users are most likely to be highest during winter or in late fall; sales to channels occur earlier. Capital equipment sales are often made near the end of a fiscal year to spend money that may not be there next year. However, as noted in Chapter 4, highly seasonal categories are less attractive due to the pressures placed on manufacturing, personnel, and cash flow. Thus, competitors in such categories look for ways to even out demand as much as possible. For example, cold remedies are marketed well before the major cold seasons to get households to stock up and lock out competing brands.

How Customers Choose

One major focus is on how customers collect (or are exposed to) information about products (e.g., advertisements, in-store personnel, brochures, magazines, or, increasingly, the Internet). In addition to defining information sources, the process used to make decisions is relevant. Often the decision process is emotional, holistic, automatic, and/or spontaneous. (Responses to the question "How did you choose it?" include "I just wanted it," "It was in stock," "The old one broke/ran out," or "I just grabbed something.") Knowing

the manner in which choice is made is relevant to strategy decisions even when the decision process is not very deliberate. Frequently, however, the process is, or can be described as, "rational." For this type of decision, customers compare alternatives on features via a multiattribute model.

The Multiattribute Model. The process of how customers make decisions has been extensively studied (Wilkie, 1990). In addition, comprehensive models have been developed that focus on consumer decision processes (Howard, 1989), information processing (Bettman, 1979), and organizational buying behavior (Johnston and Lewin, 1996). It is thus impossible to provide a comprehensive discussion here of how customers make choices. However, the multiattribute model offers a concise and practical conceptualization of customer decision making that is useful in both consumer and industrial product contexts. The multiattribute model of decision making is composed of four parts. First, the products or alternatives in a product category are assumed to be collections of attributes. Attributes can be defined in terms of physical characteristics or, as described earlier, as benefits sought. In addition, each customer is assumed to have a perception about how much of each attribute the alternatives in a product category contain. Third, each customer is assumed to place an importance value or weight on obtaining each attribute when making a choice in the category. Finally, customers are assumed to combine the attribute and importance weight information using some process, or *rule*, to develop their most preferred option in the product category. We therefore address four questions:

1. Which attributes do customers use to define a product?
2. How do customers determine how much of each attribute a brand possesses?
3. How are the importance weights determined?
4. What decision rule is used to combine the information?

Attributes. To apply the multiattribute model, one must first identify the set of relevant attributes. This is not easy; using managerial judgment alone can seriously misestimate the number and types of attributes used in making decisions. The set of attributes is useful information for the product manager, particularly for communications purposes.

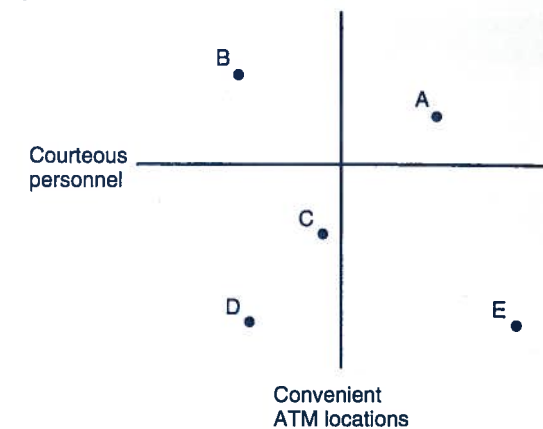
One way to collect such information is through focus group research. Participants in the focus group are first selected from the relevant segment(s). The moderator of the focus group then elicits from the set of respondents what characteristics or benefits the customers want to see in a product.

A second approach is through survey-based methods. Determining the set of attributes can be accomplished through open-ended and/or fixed-response questions. For example, to determine the set of attributes for a notebook computer, the product manager could ask the respondent to list (open-ended) or check off (closed-ended) those used in making a decision.

Perceptions. Once the attributes have been identified, the next step is to determine customers' perceptions of the amount of each attribute possessed by each brand or product option in the category. This is often done by direct questioning. Suppose that weight is

FIGURE 6-7

Bank Perceptual Map



a key attribute of a notebook computer. Then the following question could be asked: "On a 1 to 7 scale where 1 is the lightest and 7 is the heaviest, how heavy is the _____ brand of laptop computer?" This question would be asked for all the brands or models of interest to the product manager (often restricted to those the customer is familiar with). Similar questions would be used for other attributes.

An indirect approach to determining perceptions uses a marketing research methodology called *multidimensional scaling* (also referred to as *perceptual mapping*). This method provides a spatial representation of the brands in a product category based on customers' perceptions of similarity (or dissimilarity, depending on the exact method used). The characteristics used to differentiate customers' perceptions of the brands are inferred from their relative locations in the product space. The perceptions of the characteristics are inferred from their positions along the axes in the space (see Figure 3-12 for an example).

Suppose a bank manager is interested in understanding customers' perceptions of the five retail (consumer) banks in a city. The manager could first enlist a sample of respondents, perhaps 100. The task could take several forms. One approach is to take all the possible pairs of the five banks (10) and ask each respondent to rate on some scale—say, 1 to 10, with 10 being the most similar—how similar each pair is. A computer program (e.g., SAS) would then be used to locate the banks in a multidimensional space such that the number of dimensions was as small as possible but that the implied perceptual distances between the banks was replicated. Figure 6-7 shows a representative output of such a program.

Each bank is represented by a point in the two-dimensional space. The distances between the points closely replicate the information given by the respondents. For example, banks B and E are the farthest apart in the space. This means that those two banks were perceived to be the most dissimilar. The labels on the two axes (the attributes) can be determined by two methods: judgmentally based on the manager's knowledge of the market, or estimated based on other information collected from the respondents. The

FIGURE 6-8 Conjoint Analysis: Notebook Computers

Assume three attributes of laptop computer choice: Weight (3 pounds or 5 pounds) Battery life (2 hours or 4 hours) Brand name (Gateway, Compaq) Task: Rank order the following combinations of these characteristics from 1 = Most preferred to 8 = Least preferred		
Combination	Rank	
3 pounds, 2 hours, Gateway	4	
5 pounds, 4 hours, Compaq	5	
5 pounds, 2 hours, Gateway	8	
3 pounds, 4 hours, Gateway	3	
3 pounds, 2 hours, Compaq	2	
5 pounds, 4 hours, Gateway	7	
5 pounds, 2 hours, Compaq	6	
3 pounds, 4 hours, Compaq	1	

map leads to two major implications. First, the two key characteristics used by bank customers in this city are the courtesy of the personnel and the convenience of the locations of the automated teller machines (ATMs). Second, the perceived performance of the banks on those attributes differs. Bank E is perceived to have the surliest personnel, and bank D has the most convenient ATM locations. Thus, perceptual mapping can give useful information about both the characteristics being used in assessing perceived similarities and dissimilarities among products and perceptions of the products on those characteristics. While not generally thought of as a substitute for direct questioning, it can provide useful supplemental information.

Importance Weights. Like product attribute ratings, attribute importance weights can be assessed through direct questioning. Returning to the notebook computer example, a sample question could be the following: "On a 1 to 7 scale with 7 being very important, how important is weight in your purchase decision?" The same question would then be asked on the other attributes, such as speed of the microprocessor, screen viewing characteristics, and so on. The respondent could also be asked to rank order the attributes in terms of importance.

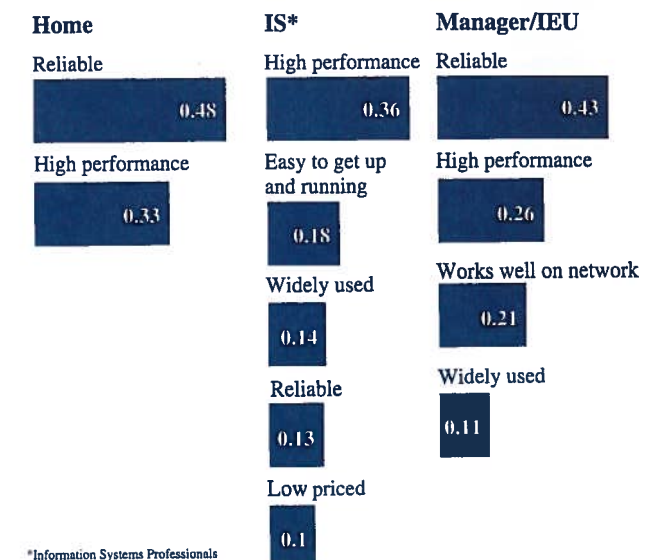
An alternative approach uses *conjoint analysis* (Green and Wind, 1975). This method permits the product manager to infer the importance of different product attributes from customer rank orderings of alternative product bundles of attributes.

As an example, assume there are three important attributes in a notebook/subnotebook computer purchase decision: weight, battery life, and brand. Assume also that each characteristic can have two different levels or values, as shown in Figure 6-8. The respondent's task is to rank order the eight combinations from the most preferred to the least preferred.

In Figure 6-8, a hypothetical response to the rank ordering task gives a 1 to the most preferred combination and an 8 to the least preferred. One combination (three pounds, four hours, and a Compaq) clearly dominates, and another (five pounds, two hours, and a Gateway) is clearly the least preferred. However, trade-offs must be

FIGURE 6-9

Importance Weight Variation by Segment

PC user demands vary by market**Significant product attributes: Desktop PCs**

Source: *Brandweek*, December 5, 1994, p. 21. © 1994 ASM Communications, Inc. Used with permission.

made for the combinations of attributes between those two options. In this case, the average rank for the three-pound options is 2.5 $([1 + 2 + 3 + 4]/4)$; for the five-pound options, 6.5; for the four-hour options, 4.0; for the two-hour options, 5.0; for the Compaq, 3.5; and for Gateway, 5.5. Looking at the differences in the average ranks, the most important characteristic to this respondent is weight (difference = 4.0), followed by the brand name (2.0) and finally battery life (1.0). While the actual analysis and design of conjoint studies are more complicated than this, the basic ideas are the same.

An example of how importance weights can vary by market segment is shown in Figure 6-9 for the personal computer market. There is a dramatic difference in the rankings of the attributes when comparing the attributes/benefits among home users, information systems (IS) professionals, and managers. Note also how price, commonly thought always to be the most important attribute, is way down the list for IS professionals and not even on the lists for the home users and managers.

Combining the Information. The most common way to combine attribute information is to use a *compensatory* rule, which simply multiplies each attribute importance weight by the attribute value and sums these terms for each person and product as in Figure 6-10. The product of importance weight times rating is simply summed down

FIGURE 6-10 Multiattribute Decision Making: Compensatory Rule

	Segment 1	Segment 2	Segment 3
Attribute A	Weight \times Rating = Score _{1a} Score _{1b} Score _{1c} Score _{1d} Score _{1e}		
Attribute B			
Attribute C			
Attribute D			
Attribute E			
Segment Score	Score _{1a} + ... + Score _{1e}		

each column of the table to get a score for each segment. A separate score is constructed for each competing brand.

Although it is difficult to determine the combination rule, if the implied ranking of the brands from the algebraic combination of importance weights and attribute perceptions does not generally match the rank order of market shares, other rules may be in effect.⁴ For example, a *lexicographic* rule first compares all products on the most important characteristic alone and eliminates those which are not at the top. A *conjunctive* rule assumes the customer sets minimum cutoffs on each dimension and rejects a product if it has any characteristic below the cutoff. A compensatory rule such as the multiattribute model implies that all attributes are considered and that weakness in one can be compensated for (hence the name) by strength in another. However, since the conjunctive rule is not compensatory, weakness on one dimension (a “requirement”) may rule out purchasing by many customers.

Customers as Problem Solvers. Customers can be described in terms of the difficulty of the problem they are attempting to solve (Howard, 1989). In extensive problem-solving (EPS) situations, customers are concerned mainly with understanding how the product works, what it competes with, and how they would use it. EPS is generally found among first-time purchasers and with products that are technologically new. Limited problem solving (LPS) occurs when the customer understands the basic functioning of the product and what it competes with, and is concerned with evaluating the brand on a small number of attributes, typically in comparison to alternatives. This is generally the approach to most large-ticket purchases when the customer has made purchases in the category before (e.g., consumer durables). The third basic type of purchase is routinized (RRB), where customers essentially follow a predetermined rule for making decisions. Most routine order purchases fall into this category, but so do many

⁴Of course, there are other explanations, such as a dominated brand being a more effective marketer in terms of distribution. Many of the brands rated highly by *Consumer Reports* do not have the highest market shares in their categories.

big-ticket items (e.g., some people always buy a Volvo). Since customers who follow this approach can be expected to ignore most information because they have already reached a decision, the implications for marketing strategy are dramatic. Product managers with a winning product that is bought routinely should make it easy for the customer to keep buying. If a product has little market share and the objective is to increase it, the product manager must “shock” the customer into considering the product to break him or her of the routine. Promotions, significant price breaks, and free samples are useful shock devices.

Why They Prefer a Product

The fourth, and in some ways the most critical, component of customer analysis examines why customers make purchase decisions. Central to this question is the concept of *customer value*: what the product is worth to the customer. Customer value thus depends on the benefits offered (from the customer’s perspective) and the costs involved (price, maintenance, etc.). The concept of value is very different from cost: An item costing only pennies to produce may be worth thousands of dollars if it solves an important problem in a timely and efficient manner, and a product that is expensive to produce may have little value. Knowing the value customers place on a product makes it much easier to make key decisions such as setting price.

The customer value of a brand is composed of three basic elements:

- 1. Importance of the usage situation.
- 2. Effectiveness of the product category in the situation.
- 3. Relative effectiveness of the brand in the situation.

Thus, customer value involves two basic notions of value: *absolute* value, which essentially assumes no competing brand exists (points 1 and 2 above) and *relative* value, which involves comparison of the product with other products. Because new markets eventually attract competitors, it is the relative effectiveness of a brand that determines its eventual share and profitability. Put differently, customer value encompasses both product form and product category competitors. It is therefore important to determine not only the usage situations for which the product category has value but also how various competitive products compare (e.g., most chemical product categories in which formulations vary eventually are chosen based on physical properties such as rigidity and stability under different temperatures).

Sources of Customer Value. Sources of value (benefits) can be classified into three broad categories: economic, functional, and psychological.

Economic. A fundamental source of value is the economic benefit a customer derives from using a product. This is a particularly relevant aspect in business-to-business situations and is often formalized as the economic value to the customer (see Appendix 6A). Essentially it is the net financial benefit to the customer from using one product versus another.

Functional. Functional value is defined by those aspects of a product that provide functional or utilitarian benefits to customers. In other words, value is provided by the performance features of a product (e.g., luggage capacity, fuel economy).

A particularly important category of functional characteristics involves service. Customers derive value from three kinds of service. Before-sales service involves providing information. Time-of-sales service facilitates purchase, such as reliable and fast delivery, installation and start-up, and convenient financial terms. After-sales service involves providing both routine and emergency maintenance. Nothing is more likely to cement a long-term customer relationship than speedy and effective reaction to a problem or more apt to destroy one than a slow and bureaucratic response. Monitoring service quality has (appropriately) become a much more important activity. More will be said about customer service in Chapter 14.

Psychological: Brand Equity. A third source of value is basically the image of the product. This includes how the product "feels" (e.g., sporty, luxurious, high-tech) and whether that feeling matches the image the customer wants to project. Price is clearly part of product image; some customers may prefer a high price (either because they view price as a signal of quality or engage in conspicuous consumption), whereas others prefer a low price. The importance of image (as opposed to functional attributes) was highlighted by adverse reaction to Coke's formula change (even though it was preferred in blind taste tests) and the strong positive reaction to the reintroduction of Classic Coca-Cola.

Recently, partly inspired by a wave of corporate takeovers, the value of the brand name per se has received much attention (Aaker, 1991, 1996). To a customer, *brand equity* is the value of a product *beyond* that explainable by economic and functional attributes. (Brand equity also represents value to the manufacturer, which is discussed in Chapter 8.) It can be represented by the premium a customer would pay for one product over another when the economic and functional attributes are identical.

A number of methods exist for measuring brand equity at the customer level including Y&R's Brand Asset Valuator, Research International's Equity Engine, and Millward-Brown's Brand Z. Basically they break down into four broad categories (see also Aaker, 1996; Keller, 1998):

1. *Awareness.* Being aware of a brand is usually a requirement for its purchase (at least for sober customers) and tends to lead to more favorable opinions by reducing the risk associated with a familiar option.
2. *Associations.* Images related to overall quality as well as specific product attributes and user characteristics (e.g., young, hip) impact the reaction to a brand.
3. *Attitude.* Overall favorability toward a brand is a critical part of brand equity. A special form of this is inclusion in the consideration set (that is, the willingness to consider buying the brand, similar to being on an approved supplier list in business-to-business marketing) or put differently, acceptability.
4. *Attachment.* Loyalty to a brand is the strongest type of equity (although in the extreme case of addiction it may have some undesirable consequences), and

most beneficial for sellers. In the extreme (100 percent retention), it guarantees a nonending stream of income.

We discuss brand equity and its implications in more detail in Chapter 8.

Manifestations of Customer Value. A variety of signs of the value of a product are evident even without special efforts to measure them:

Price. Price is the company's assessment of the product's value.

Price sensitivity. A product with constant sales when prices increase generally is of greater value than one for which demand slumps.

Satisfaction. Survey-based satisfaction measures are standard practice in my businesses (e.g., course evaluations).

Complaints and compliments. The number of complaints or compliments the company receives indicates the product's value.

Word-of-mouth. Although often difficult to track, spoken and written comments provide a useful subjective assessment of a product's value. (Monitoring chat rooms and bulletin boards on the Web is a useful way to track word-of-mouth.)

Margin/profit contribution. Generally, higher margins indicate partially monopolistic positions due to greater communicated value.

Dollar sales. Total dollar sales provide an aggregate measure of the value of a product as assessed by the market.

Competitive activity. Competitive activity such as new-product introductions indicates that the total gap between customer value and company costs is sufficiently large to allow for profits even when more companies divide the market.

Repeat purchase rate. High loyalty indicates high brand value.

Assessing the Value of the Product Category. Many ways can be devised to estimate the value of a product category. One particularly useful method focuses on the value of different uses or applications of a product.

1. Determine the uses of the product. Like the substitution-in-use approach discussed in Chapter 3 for generating generic competitors, a first step is to determine the present and potential uses to which a particular product category can be put.
2. Estimate the importance of the uses. This estimate could focus on individual customers or market segments and may simply be projected sales to the segment.
3. List competing products for the uses.
4. Determine the relative effectiveness of the product category in each usage situation.

An overall value of the product category can be estimated by summing over all uses of the importance of the use times the relative effectiveness of the product category.

FIGURE 6-11 Personal Computer Product Category Value

Use	(IMP) Importance	Competitive Products	(REL) Relative Effectiveness	Category Value (IMP) × (REL)
Video games	Some 20	TV attachments, board games	Very good	High
Bookkeeping	None 1	Accountant, service bureau, "books"	Marginal	Low
Learning skills	Very low 4	Books, school	Inferior	Low
Data analysis	Large 65	Large-scale computer, time sharing, consultant, calculator	Good	High
Report preparation	A little $\frac{10}{100}$	Typewriter, word processor, secretarial service	OK	Fairly low

A hypothetical example of this approach, based on the personal computer category, appears in Figure 6-11. Rather than using numbers, this scale uses adjectives. Although it is fairly easy to structure a table like Figure 6-11, some of the entries will be hard to quantify. However, the main value of the exercise is to generate broad indicators toward which particular uses of the microcomputer should be targeted.

Assessing the Value of the Brand/Product/Service. Assessing the total value of a brand can be done indirectly. A high value brand has high share, high repeat purchase rate, low elasticity with respect to price, and limited competitive brand shopping. Using customer responses to estimate the value of a brand generally involves direct ratings. This includes several different approaches:

1. *Direct ratings* on a scale (e.g., "How good is X for use Y?") for competing products. Remember we are generally interested in relative and not absolute value. Therefore, an average of 4 on a 5-point scale indicates good value if the other products are getting 2s and 3s, but little value if the other products are getting averages of 4.5 and 4.8.
2. *Constant sum ratings across brands*, such as "Please rate the following brands by dividing 10 points among them":

Brand A _____

Brand B _____

Brand C _____

Brand D _____

Total 10

FIGURE 6-12 Dollar Metric Example: Soft Drink Preference

Pair of Brands (more preferred brand circled)	Amount Extra Willing to Pay to Get a Six-Pack of the More Preferred Brand (cents)
Data	
(Coke) Pepsi	2
(Coke) 7UP	8
(Coke) Dr. Pepper	5
(Coke) Fresca	12
(Pepsi) 7UP	6
(Pepsi) Dr. Pepper	3
(Pepsi) Fresca	10
7UP (Dr. Pepper)	3
7UP (Fresca)	4
(Dr. Pepper) Fresca	7
Analysis	
Coke:	+ 2 (versus Pepsi) + 8 (versus 7UP) + 5 (versus Dr. Pepper) + 12 (versus Fresca) = 27
Pepsi	- 2 + 6 + 3 + 10 = 17
7UP	- 8 - 6 - 3 + 4 = -13
Dr. Pepper	- 5 - 3 + 3 + 7 = 2
Fresca	- 12 - 10 - 4 - 7 = -33

3. *Graded paired comparisons*, which require customers to indicate which of a pair of products they prefer and by how much. This is often done in terms of dollar amounts (Pessemier, 1963), as shown in Figure 6-12.
4. *Conjoint analysis* of customer ratings of products described in terms of attributes, including price and brand name. Through analysis (basically regression analysis), the relative importances of the attributes, as well as the values of different levels of these attributes, are determined.

How They Respond to Marketing Programs

In addition to the product itself, sensitivity to and preference for prices (and means of payment), distribution and availability (including the effect of direct marketing), advertising, promotion, and service are fundamental aspects of a market. Moreover, sensitivity typically varies by customer and at least a segment-level analysis is usually called for. Methods for assessing sensitivity include:

1. *Expert judgment*, using the knowledge of managers, the salesforce, etc.
2. *Customer survey-based methods*, including both direct questioning (e.g., "How important is . . . ?") and more subtle approaches such as conjoint analysis.

3. *Experiments*, in both controlled settings (e.g., in shopping malls or specially designed stores or labs) and actual markets.
4. *Analyses of past data*, comparing results across markets, or where individual customer record data are available (e.g., scanner data) at the individual level. Such analysis often uses techniques such as regression analysis to predict sales as a function of mix elements or logit analysis (basically a type of regression) to assess the impact of mix elements on market share or individual choice probabilities.

Assessing sensitivity to elements of the marketing mix is a large, ongoing task. The output of this assessment has implications primarily for the tactical/programmatic elements of marketing (e.g., how much to spend on advertising). Since this assessment requires specialized data not readily available outside the company, we do not discuss mix assessment in detail here.

Will They Buy It (Again)?

A critical issue involves whether customers will purchase the product in the future, which heavily depends on their satisfaction with the product.

Satisfaction. Perhaps the most obvious trend in business in the late 1980s and early 1990s was the religious zeal with which quality programs were promoted, especially in the United States. Providing quality in order to satisfy current customers and retain them in the future is a logical consequence of the basic principle of marketing, to create and maintain customers. So-called relationship marketing also stresses the long-term value of a customer where a single transaction (sale) is not the ultimate goal.

Quality is ultimately measured in terms of customer satisfaction. Further, satisfaction has a strong relative component to it. (Are customers of a certain product category more or less satisfied than those of a different but potentially substitutable one? Are customers of my company's product more or less satisfied than customers of a competitor's?)

The direct measurement of satisfaction has evolved to consider several aspects:

1. Expectations of performance/quality.
2. Perceived performance/quality.
3. The gap between expectations and performance.

Much of the early work on satisfaction focused on the gap between expectations and performance, and a widely used scale called SERVQUAL (Parasuraman, Zeithaml, and Berry, 1988) was developed based on it. Subsequently, however, emphasis has also been placed on the direct impact of expectations and performance on satisfaction as well as the effect of expectations on perceived performance (Anderson and Sullivan, 1993; Boulding, Staelin, Kalra, and Zeithaml, 1992). Thus satisfaction is now typically modeled as a function of (1) expectations, (2) performance, and (3) the difference between expectations and performance (with "negative disconfirmation," when performance falls short of expectations, having a much stronger impact than positive disconfirmation). In

assessing satisfaction it is important to compare satisfaction with one's own company with that of (1) other companies in the industry/category and (2) with other companies in general, especially those in categories that are potential substitutes.

Of course indirect measures of satisfaction abound, including word-of-mouth comments, complaints, and, perhaps most importantly, repeat purchase (or lack thereof). The basic reason for caring about satisfaction is that it leads to customer retention. Hence, measures of intended or actual repeat purchasing provide a useful way to simultaneously measure satisfaction and its impact. Note that it is possible for customers to be satisfied but not repurchase due to, among other things, poor product supply, variety seeking or multiple sourcing, and large promotional deals. Similarly they may be unsatisfied but continue to purchase, for example when dealing with a monopoly. Several authors have assembled satisfaction data across industries and demonstrated its link to retention (Fornell, 1992) and profitability (Anderson, Fornell, and Lehmann, 1994).

Intentions. Intentions are imprecise predictors of future purchase (as in he or she "had good intentions but . . ."). Still they provide early signs of future sales. In fact, surveys of customers (asking "Would you buy _____?" and/or "How much _____ will you buy?") are a staple input to sales forecasts, especially for industrial products, and we discuss them in greater detail in Chapter 7.

The Long-Term Value of Customers

A fundamental issue in marketing strategy is the long-term value of a customer to the firm. Decisions about customer acquisition and retention (i.e., will they buy it again) as well as the level of effort to direct toward each customer depend on the future net revenues expected from them. While measures such as size, wealth, and past purchases provide crude estimates of worth, the value of a customer is the discounted sum of future net revenue of the customer. The net revenue depends on the amount and type of transactions (i.e., volume and margin) as well as the cost to service (retain) the customer.

On a direct cost basis, not all customers are profitable. Often small accounts do not generate sufficient revenue to cover the cost of servicing them, although the cost of dealing with large accounts often makes them unprofitable as well. In fact, some companies estimate that 80 to 90 percent of their customers are nonprofitable, leading to such contested practices as "slamming" (transferring accounts to other companies without their consent). Credit card holders who pay off their balances on time, cable subscribers in remote areas, and "high service" customers who heavily use toll-free numbers are common examples of unprofitable customers.

On the other hand, customers that are unprofitable in the short run may be very profitable in the long run. While the cost of acquiring a customer (solicitation plus special deals) is typically greater than first year profits for life insurance, magazine subscriptions, and many other businesses, lower long-run maintenance costs (due to high repeat rates) lead to strong positive returns in subsequent years. Calculating the value of a customer is straightforward, although heavily influenced by assumption. We discuss this concept in detail in Chapter 14.

Segmentation

Desirable Criteria for Segments

Given the tremendous number of potential bases for segmentation, a pertinent question is which one to use. Actually, several can be used in combination, so the question is really: What makes a good basis for segmentation? While there is no single way to say what is best (anyone suggesting there is probably doesn't understand the problem or is selling a particular segmentation method), the following six criteria provide a useful standard for evaluation:

1. **Sizable.** Segments must be of sufficient size in terms of potential sales (but not in terms of number of customers; some customers may be large enough to consider on their own) to be worth worrying about. As a rule, billion-dollar companies don't care much about J.R. Smith at 1188 Maple Street, or all the people on Maple Street for that matter.
2. **Identifiable.** Segments should be identifiable so that when presenting results they can be referred to by more pleasing titles than segment A and segment B (e.g., the 35-to-50 segment, the sports-minded, companies in New York). More importantly, the identity of the segments provides an aid to strategic and tactical decisions.
3. **Reachable.** It may be sufficient for strategic purposes to identify a segment. For purposes of planning the marketing mix (e.g., advertising), however, it is useful to be able to target efforts on a segment. A sports-minded segment tends to be reachable through the media (e.g., *Sports Illustrated*, ESPN), whereas people who prefer the color blue, though identified, may be harder to reach efficiently (except by labels on blue towels, or by copy that employs the color blue).
4. **Respond Differently.** Ideally, segments should respond differently to at least some of the elements of the offering. If all segments respond the same, then no specialized programs can be used. For example, some customers may be sensitive to advertising but not price, whereas others are concerned about price but unaffected by advertising, and still others care about a single attribute such as downtime. The sensitivity to changes in market offering forms a useful basis for both describing the overall market and defining segments. It also makes the "why they buy" part of the analysis particularly crucial.
5. **Coherent.** When interpreting a segment, it is implicitly assumed that all members are homogeneous. This is always violated to some extent. What is important is that the average member of a segment be reasonably close to the rest of the members. Hence, an important conceptual requirement of a segment is that the within-segment variation in behavior be (much) smaller than between-segment variation. (This desired condition is often operationalized as the basis for statistical tests for determining the number of segments.)
6. **Stable.** Since future plans are based on past data, segments (and hopefully but not necessarily the members of those segments) should be fairly stable over time.

Methods for Market Segmentation

Many of the methods developed for market segmentation, particularly by marketing academics, are highly technical and are not in widespread use among product managers. In this section, we focus on three methods that are simple to apply and for which there is easy-to-use computer software: (1) cluster analysis, (2) tabular analysis, and (3) regression analysis. We also briefly describe a fourth approach, latent class analysis. We assume the product manager has customer data from surveys or other sources measuring both descriptive information and information about behavior toward the product in question. Again, we interpret the term *customer* broadly to imply that data should be collected from former and potential as well as current customers.

A basic approach to segmentation analyses relates information about the two kinds of segmentation variables: descriptors and behavioral variables. Neither type by itself is very useful. We know that approximately 50 percent of the population is men and 50 percent women. This information alone is not helpful to the product manager because it does not indicate whether men or women have a greater propensity to buy our product. Alternatively, suppose we know that 20 percent of the population consists of heavy buyers, 40 percent of medium buyers, and 40 percent of light buyers. Again, this information is not very useful if we do not know who these buyers are (in terms of income, geography, and so forth); that is, we have no way to reach any of the groups. As a result, the methods on which we focus relate descriptor and behavioral data about customers in different ways to form market segments.

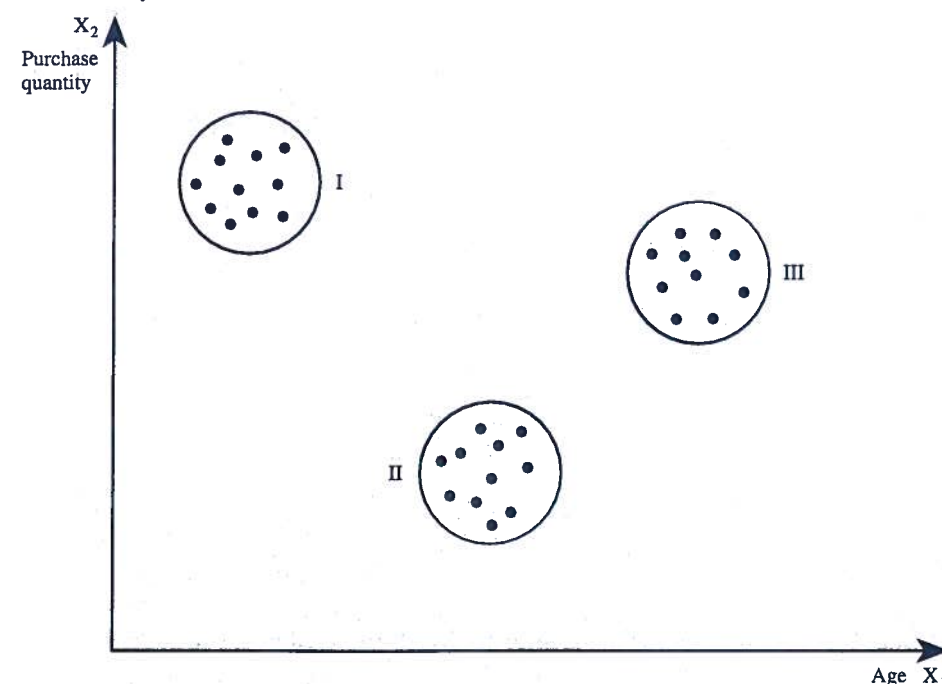
Cluster Analysis. One way to generate segments is to collect data about the descriptor and behavioral variables from a sample of customers and then form groups by means of cluster analysis. Cluster analysis examines the values of the variables for each respondent (from a sample of customers) and then groups respondents with similar values. Consider Figure 6-13. Each dot represents a combination of factors, say, age (X_1) and purchase quantity (X_2). In this case, three obvious clusters emerge. These clusters are appealing in that the members of each cluster are similar to one another and different from members of other clusters in terms of age and purchase quantity. A product manager would conclude from this analysis that the youngest customers purchase the most, oldest customers the second most, and middle-aged people are not interested. Cluster analysis programs are widely available in commercial computer software packages such as SAS and SPSS. (Unfortunately, such clear clusters rarely emerge.)

For example, a regional phone company employed cluster analysis to understand its residential customers. The company collected information on descriptors, attitudes, and behavior (usage was measured in dollars) and formed six segments based on clustering those households that "looked the same" based on the variables:

1. Low income/blue collar: "Fledglings."
2. Frugal/retired: "Thrifties."
3. Contented middle class: "Contenteds."
4. Aspiring middle-class status seekers: "Climbers."

FIGURE 6-13

Cluster Analysis Illustration



5. Technology-driven strivers: "Techies."

6. Contented upper middle class: "Executives."

A more detailed profile of the segments is shown in Figure 6-14.

Mobil also applied cluster analysis to gasoline buyers to tailor different stations to neighborhoods with different profiles and needs (Sullivan, 1995). The company identified five segments of gasoline buyers:

1. Road warriors: higher-income, middle-aged men who drive 25,000 to 50,000 miles per year, buy premium gas with a credit card, and buy sandwiches and drinks from the convenience store (16 percent of buyers).
2. True blues: men and women with moderate to high incomes who are loyal to a brand and sometimes to a particular station (16 percent).
3. Generation F3 (fuel, food, and fast): upwardly mobile men and women, half under 25 years old, who are constantly on the go; drive and snack a lot (27 percent).
4. Homebodies: usually homemakers who shuttle their kids around during the day and buy gas from whatever station is along the way (21 percent).
5. Price shoppers: not loyal to a brand or station, rarely buy premium (20 percent).

FIGURE 6-14 Cluster Analysis: Phone Company Market Segmentation Scheme

	<i>Fledglings</i>	<i>Thrifties</i>	<i>Contenteds</i>	<i>Climbers</i>	<i>Techies</i>	<i>Executives</i>
Mean age	37	51	44	43	38	40
Mean income	\$26k	\$27	\$37k	\$31k	\$40k	\$48k
Occupation	Blue collar	Retired/blue collar	Administrative/professionals	Administrative/sales	White collar	White collar
Education	14	12	14	16	18	18
Married	60%	72%	76%	65%	33%	72%
Children	44%	38%	51%	54%	75%	33%
Mobility	High	Low	Medium	Medium	High	Low
Home value	\$70-85k	\$60-80k	\$70-85k	\$60-80k	\$80k+	\$90k+
Dual income	Low	Medium	Medium	High	Highest	Medium
Number of phones	Low	Low	Medium	Medium	High	High
Type of phones	Basic/standard	Basic/standard	Medium mix	Medium mix	All types	All types
Monthly bill	Low	Low	Medium	Very high	Very high	Very high
Technology adoption	Late adopters	Laggards	Late adopter	Early adopter	Innovator	Early adopter
Purchase criteria	Value/money	Security	Convenience	Status	Environmental control	Quality
Application	Social interaction	Safety and protection	Social interaction	Social interaction	Personalized systems	Time saving

Most gas companies have targeted the last group. However, Mobil emphasized better service and amenities to customers in the first two segments and was able to charge 2 cents more per gallon than competitors in some markets.

A third example highlights the use of a geodemographic system called PRIZM (Potential Rating Index by Zip Market), marketed by Claritas Corporation. PRIZM's basic analysis is performed on U.S. ZIP codes. Based on the 1990 census, the PRIZM system examined the means of a set of demographic variables for all of the nearly 40,000 U.S. ZIP codes. Using the demographic variables, the ZIP codes are then clustered into 62 different groups. These 62 groups are given catchy names based on the mean levels of the variables, such as "Norma Rae-ville," "Cashmere & Country Clubs," and "American Dreams." The final crucial step, of course, is to relate membership in the geodemographic clusters to purchasing of various products and services (the behavior variable).

Figure 6-15 shows an application of PRIZM to the beer market (Martin, 1994). The graphs clearly indicate the different amounts of market potential for various kinds of beer in the various PRIZM segments. Families in the "Blue Blood Estates" and "Urban Gold Coast" clusters are particularly good targets for imported beer (they are about seven times more likely to drink imported beer than malt liquor), whereas "Southside City" families show the reverse behavior.⁵

⁵There is a "chicken and egg" problem here; Do "Southside City" families have a naturally high propensity to drink malt liquor, or is it high due to intensive marketing efforts? Products developed for particular segments and heavily marketed to them will naturally have higher purchase incidence rates unless there is a total market/product mismatch. The reader should also note the ethical implications of target marketing by demographic/ethnicity variables for certain kinds of products, such as malt liquor.

FIGURE 6-15

Prizm Geodemographic Segmentation

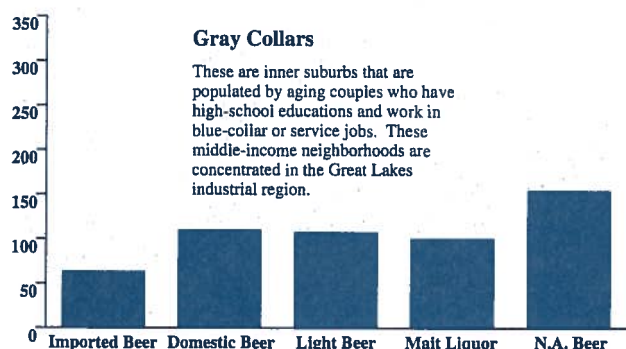
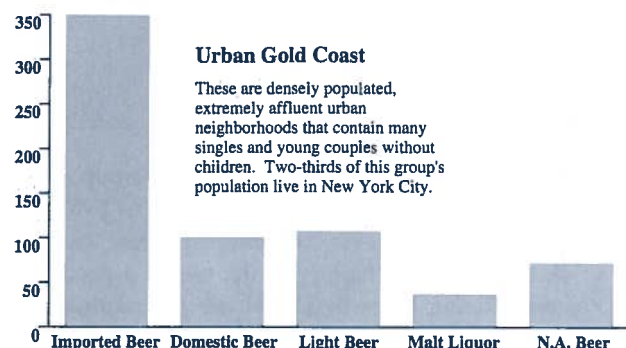
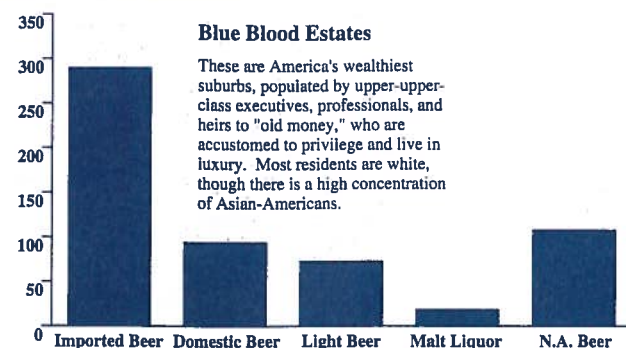


Figure 6-16 provides another example from Strategic Mapping, Inc.'s ClusterPLUS 2000 for the disposable diaper market. This analysis developed 60 segments using data similar to that used by PRIZM. Figure 6-16 provides the number of households in each segment, the percentage of U.S. households in the segment (%Base), the estimated number of disposable diapers used in one day in the segment (Usage), the percentage of U.S. daily disposable diaper use (% Usage), the average number of diapers used per household in that segment (Avg. Use), and an index that is the ratio of %Usage/%Base and gives some idea about the usage rate of that segment relative to the size of the segment. The indexes are rank ordered for easy analysis by the product manager. While this index obviously is not the only criterion for choosing a target segment (e.g., no data by brand are shown), the information is a useful part of an overall picture of consumer behavior in the disposable diaper category.

Industrial customers can also be segmented on the basis of reactions to marketing mix variables (Rangan, Moriarty, and Swartz, 1992). For example, a large industrial product company segmented its national accounts based on the trade-offs made between price and service to form four segments:

Programmed buyers: small customers that do not consider the product important and make routine purchases.

Relationship buyers: small buyers, loyal to the supplier, that pay low prices and obtain high service levels.

Transaction buyers: large buyers for which the product is important and that obtain price discounts, expect high service levels, and switch suppliers.

Bargain hunters: large buyers that get the lowest prices and the highest service.

Using electronic scanner data, product managers can segment by store. For example, Kraft can alter the mix of flavors of cream cheeses sold by supermarkets across different neighborhoods. Retailers also can use this analysis. Target's store on Phoenix's eastern edge sells prayer candles (the area is heavily populated by Catholic Hispanics) but no child-toting bicycle trailers. The Target 15 minutes away in affluent Scottsdale sells the trailers but no portable heaters. Heaters can be found 20 minutes south in Mesa, which has a cooler climate (Patterson, 1995).

Of course segmentation is not a new topic. In February 1949 critic Russell Lynes produced a segmentation of American consumers that was both insightful and led to a Broadway show (Figure 6-17).

Tabular Analysis. This analysis uses categorical variables constructed from customer membership in a category. For example, surveys usually ask respondents to identify the range in which their incomes fall, such as "\$20,000-\$29,999," "\$30,000-\$39,999," and so on, or what their favorite brand is. Sometimes surveys ask questions that are continuously "scaled," for example, "How many times did you go to the movies last month?" The answers can then either be analyzed as given or be placed in categories (e.g., 0-2 times, 3-5 times, 6 or more).

As an illustration, consider the data in Figure 6-18. These data were taken from a survey of 1,004 users of cranberry sauce (DeBruicker, 1974). The descriptor variables,

FIGURE 6-16 ClusterPLUS 2000 Product Potential Report

Item:	S1150 Number of Disposal Diapers Used in HH on Avg Day					
Market:	U.S.					
Demographic Base:	Households					
Group Set:	Clusters					
Description	Base Count	% Base	Usage	% Usage	Avg Use	Index
Totals: U.S.	96,976,894	100.00	44,435,425	100.00	0.46	100
C54: Young Blacks with Kids	796,378	0.82	656,588	1.48	0.82	180
S45: Low Income Younger Blacks	794,712	0.82	623,785	1.40	0.78	171
C40: Younger Mobile Singles	1,551,509	1.60	1,072,648	2.41	0.69	151
U10: New Families, New Homes	1,794,370	1.85	1,208,366	2.72	0.67	147
S22: Young Families Dual Income	2,545,890	2.63	1,696,654	3.82	0.67	145
S07: High Inc, Young Families	1,582,765	1.63	1,026,304	2.31	0.65	142
T53: Low Income Ethnic Mix	2,408,568	2.48	1,532,643	3.45	0.64	139
U44: Young Black Families	1,097,859	1.13	694,500	1.56	0.63	138
U48: VYng BCollar Hispanic Fams	887,710	0.92	544,265	1.22	0.61	134
C57: Black Lowest Inc Fem Hd HH	1,102,997	1.14	670,655	1.51	0.61	133
S35: Avg Age/Inc Flue Collars	3,111,554	3.21	1,831,753	4.12	0.59	128
C27: Yng Avg Inc, Hispanics Apts	1,606,595	1.66	922,631	2.08	0.57	125
R26: Yngr Setld BCollar Fams	2,202,399	2.27	1,224,826	2.76	0.56	121
U30: Yngr Homeowners L Val Home	1,777,653	1.83	946,531	2.13	0.53	116
R47: Below Avg Inc Work Couples	3,295,708	3.40	1,732,530	3.90	0.53	115
U18: Yngr Hsp/Asian Homeowners	1,336,855	1.38	696,558	1.57	0.52	114
U23: Yngr Families Lo Val Homes	2,342,629	2.42	1,195,549	2.69	0.51	111
C52: Mid-Age Old Apts	1,111,753	1.15	562,416	1.27	0.51	110
T37: Below Avg Inc Blue Collar	2,726,056	2.81	1,343,793	3.02	0.49	108
R28: Setld Couples Lo Val Homes	5,259,551	5.42	2,547,153	5.73	0.48	106
U46: Above Avg Age Low Inc/Rent	1,281,639	1.32	597,541	1.34	0.47	102
C55: Low Inc Mobile Hispanics	1,725,271	1.78	800,347	1.80	0.46	101
R43: Below Avg Inc Blue Collars	3,991,458	4.12	1,802,116	4.06	0.45	99
S03: Well Educated Professional	1,972,176	2.03	877,473	1.97	0.44	97
S50: Very Young Hispanics	560,158	0.58	243,992	0.55	0.44	95
S12: High Inc Settled Families	2,208,503	2.28	960,122	2.16	0.43	95
U08: Hi Inc Urban Professionals	1,390,450	1.43	593,088	1.33	0.43	93
U04: Upscale Urban Couples	1,635,493	1.69	671,429	1.51	0.41	90
C29: Avg Age & Inc Few Kids	1,731,043	1.79	700,570	1.58	0.40	88
C25: Young WCollar Singles Apts	2,472,066	2.55	954,393	2.15	0.39	84
U31: Very Young Apt Dwellers	3,196,517	3.30	1,202,506	2.71	0.38	82
S05: Younger Affluent w/Kids	1,812,746	1.87	676,769	1.52	0.37	81
T19: Above Avg Age White Collar	2,141,629	2.21	793,668	1.79	0.37	81
U24: Avg Inc Apts Fewer Kids	1,728,593	1.78	611,974	1.38	0.35	77
U36: Avg Income Hispanics	1,098,132	1.13	380,782	0.86	0.35	76
U14: High Inc WCollar Apt/Condo	2,741,736	2.83	945,426	2.13	0.34	75
C34: Younger, Hispanics/Asians	2,031,995	2.10	699,422	1.57	0.34	75
S13: WCollar High Value Homes	1,539,106	1.59	519,431	1.17	0.34	74
S21: Suburban Married Couples	1,989,228	2.05	619,096	1.39	0.31	68
S38: Retired Homeowners	1,187,663	1.22	368,475	0.83	0.31	68
R06: Rural Affluents, New Homes	919,158	0.95	281,294	0.63	0.31	67
C15: Single Prof High Rent Apts	2,159,119	2.23	634,909	1.43	0.29	64
S09: Mature Couples Profs	1,139,545	1.18	321,101	0.72	0.28	61
R16: Younger Couples with Kids	2,509,079	2.59	681,097	1.53	0.27	59
S02: Mid-Age Affluent w/Kids	718,314	0.74	194,525	0.44	0.27	59
S01: Established Wealthy	543,731	0.56	135,722	0.31	0.25	54
C17: Prof & Retirees Apt/Condo	1,266,237	1.31	274,325	0.62	0.22	47
C11: Ctr City Affluent Few Kids	968,301	1.00	185,212	0.42	0.19	42
*G59: GQtrs: Military	45,649	0.05	29,083	0.07	0.64	39

*Results should be viewed with caution—insufficient sample size.



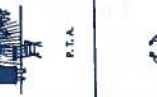












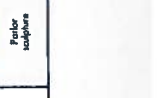























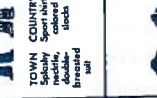






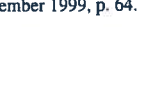





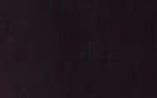
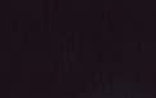
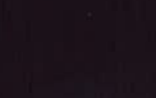





Note: Calculations are based on Source Market Usage.

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Source: Strategic Mapping, Inc. based upon Simmons Market Research Bureau data.

FIGURE 6-17

Taste Segmentation

	CAUSES	CAUSES	CAUSES	CAUSES
				
				
				
				
				
				
				
				
				
				
				
				
				
				
				
				

Source: American Heritage magazine, December 1999, p. 64.

FIGURE 6-18 Raw Data: Cranberry Sauce Usage

Cooking Attitude	Heavy Users	Medium Users	Light Users	Total (now marginal)
Convenience oriented	81	144	74	299
Enthusiastic cook	97	115	45	257
Disinterested	35	108	127	270
Decorator	45	96	37	178
Column total (marginal)	258	463	283	1,004

located in the leftmost column, are based on some prior analyses of data concerning attitudes toward cooking. These four categories are "convenience oriented," "enthusiastic cook," "disinterested," and "decorator." The descriptor variable is sometimes referred to as the *independent* variable. The behavioral categories, located across the top, are divided into three groups based on self-reported usage: heavy, medium, and light. This variable is referred to as the *dependent* variable. Entries in the table or cells indicate the number of consumers who simultaneously satisfy both a descriptor group and a behavioral group. In other words, 81 people were both heavy users of cranberry sauce and convenience oriented. The row sums and the column sums are called *marginals*.

The basic issue facing the product manager, assuming she or he is interested in understanding how to segment the market based on the behavioral variable of usage quantity, is whether attitude toward cooking is a useful variable. Product managers have many descriptor variables to choose from, not to mention several behavioral variables. An important task is to sift through the candidate descriptors to find some that are useful to describe the heavy, medium, and light buyers.

Before analyzing the results in great detail, it is useful to first determine if there is a *statistically significant* relationship between the independent variable, cooking attitude, and the dependent variable, usage quantity. The most common and simplest approach to this task is a *chi-square* test. In this test, each cell based on the survey results (e.g., Figure 6-18) is compared to an *expected* cell size or the number of people that would be expected in that cell if attitude toward cooking were independent of usage quantity. The expected cell size can be calculated by multiplying the marginal for the row in which the cell is located by the marginal for the column in which the cell is located and dividing by the total sample size. For example, the expected cell size for the convenience-oriented-heavy usage cell is $(299 \times 258)/1,004 = 77$. Then the chi-square value is determined by taking the sum over all cells of the $(\text{observed} - \text{expected})^2/\text{expected}$. For Figure 6-18, the chi-square value is 86. Combined with the number of degrees of freedom of the table (the number of rows minus 1 times the number of columns minus 1) and the significance level of the test, it is compared to a table of chi-square values found in any statistics book. In this example, the chi-square value of 86 with 6 degrees of freedom exceeds the table value of 12.6 at the

FIGURE 6-19 Cranberry Sauce Usage Percentages

Cooking Attitude	Heavy Users	Medium Users	Light Users
Convenience oriented			
Row %	27%	48%	25%
Column %	31	31	26
Enthusiastic cook			
Row %	38	45	18
Column %	38	25	16
Disinterested			
Row %	13	40	47
Column %	14	23	45
Decorator			
Row %	25	54	21
Column %	17	21	13

95 percent confidence level. Thus there is a significant relationship between consumers' attitudes toward cooking and their reported cranberry sauce usage levels.⁶

A second step in the analysis is to better understand the nature of the relationship between the two variables⁷ by calculating percentages. The two most common ways to calculate percentages are to divide each cell by its row marginal to obtain row percentages or to divide each cell by its column marginal to obtain column percentages. Figure 6-19 shows the row and column percentages for the cranberry sauce data.

The row percentage indicates what percentage of the row category customers are in the column group. In the example, 27 percent of convenience-oriented consumers are heavy users. The column percentage indicates what percentage of the column category is in the row group. In the example, 31 percent of heavy users are convenience oriented. Of course the product manager must interpret these two types of percentages differently.⁸

Assume the manager is interested in medium users because heavy users are saturated and light users probably cannot be convinced to consume more cranberry sauce. Which customers should the product manager pursue? One obvious group is convenience-oriented cooks, as this group has the largest number of medium buyers (31 percent) and is the second most "concentrated" (48 percent of them are medium

⁶The chi-square tests from different descriptor variables can be compared to see which of these the product manager should consider further in the segmentation analysis. This is more complicated than it sounds, as the chi-square values of tables with different numbers of rows and/or columns (degrees of freedom) cannot be directly compared. One alternative is to standardize all the tables to the same size. A second alternative is to use a computer program such as SAS that prints out the exact level of significance of each chi-square result and rank orders the descriptors by this number.

⁷Cross-tabular analysis can easily be extended to tables with more than one independent variable. The same logic for the chi-square test holds.

⁸To see this more clearly, consider the descriptor "men" and the behavioral variable "reads *Playboy* magazine." In this case, a large percentage of *Playboy* readers are men, but a small percentage of men are *Playboy* readers.

users). Enthusiastic cooks might also be targeted, as they are the largest group of heavy users (38 percent).

Note that the cranberry sauce example illustrates the use of psychographics as potential segmenting variables. However, since media are not all measured by psychographics, an additional cross-tabular analysis matching demographic or socioeconomic variables with the lifestyle variable may be necessary for lifestyle segmentation. In other words, if the product manager wishes to target convenience-oriented customers, it is useful to know income, geographic, and other information about them to implement the segmentation strategy.

Regression Analysis. Like cross-tabular analysis, regression analysis is used when the product manager can specify an explicit relationship between a dependent (behavioral) variable and one or more descriptor (independent) variables.⁹ However, unlike cross-tabular analysis, regression theoretically assumes a continuously measured dependent variable. Using the cranberry sauce illustration, if the dependent variable is reported usage in number of cans rather than categories of consumption, then regression will be more appropriate.

Suppose we believe that income and family size are key segmentation variables in addition to the four categories of cooking attitudes. Assume three categories of income (low, medium, and high) are reported on the survey as well as the actual number of people in the family. We can then specify a *model* of the following form:

$$\text{Usage} = f(\text{CO}, \text{EC}, \text{DI}, \text{DE}, \text{LOWY}, \text{MEDY}, \text{HIGHY}, \text{FAMSIZE}),$$

where the dependent variable is the reported usage rate of cranberry sauce and the independent variables are the descriptors: convenience oriented, enthusiastic cooks, disinterested, decorator, low income, medium income, high income, and family size, respectively.

Generally, a person can be in only one category of cooking attitude and one category of income. In addition, assume these two variables cannot be represented by continuously measured numbers such as reported usage (number of cans) and family size (number of people). Therefore we need to create *dummy variables* to represent the cooking attitude and income variables. These variables are simply 0 or 1, indicating membership in one of the categories.

Figure 6-20 provides a hypothetical representation of the survey responses of five individuals. The first column contains values of the dependent variable, usage of cranberry sauce in number of cans. The next four columns represent cooking attitude. However, each respondent can have 1 in only one of the columns and must have a 1 in one of them because the categories are mutually exclusive and collectively exhaustive. The next three columns represent the income variable. Finally, family size is reported as the actual number.

⁹We assume in this section that the reader has some working knowledge of regression analysis.

FIGURE 6-20 Cranberry Usage Data by Person

Person	Cranberry Sauce Usage (Number of cans)	Cooking Attitudes				Income			Family Size
		CO	EC	DI	DEC	LO	MED	HI	
1	5	0	1	0	0	0	1	0	4
2	2	1	0	0	0	0	0	1	3
3	0	0	0	1	0	1	0	0	5
4	6	0	0	0	1	0	1	0	4
5	3	1	0	0	0	1	0	0	3

Due to statistical (and logical) restrictions, if a dummy variable has n categories, only $n-1$ are needed in the regression. Therefore, rewriting the regression model in equation form, we obtain

$$\text{Usage} = a + b\text{CO} + c\text{EC} + d\text{DI} + e\text{LOWY} + f\text{MEDY} + g\text{FAMSIZE},$$

where a to f are regression coefficients estimated using the data in Figure 6-20 and some computer software (e.g., Excel).

The interpretation of the coefficients differs between the continuously measured variable, FAMSIZE, and the dummy variables. The coefficient g is interpreted in the usual way: For a one-person change in family size, usage changes by g units. For example, if g is positive, a one-person increase (decrease) in family size is predicted to increase (decrease) usage by g units. The coefficients b , c , d , e , and f , however, are interpreted differently. Recall that these variables are measured either as 0 or 1 depending on membership in that category. For each set of dummies, a coefficient is interpreted as the *contrast* from the omitted category. For example, b , the coefficient of the dummy variable "convenience oriented," is interpreted as the estimated difference in cranberry sauce usage between a person who is convenience oriented versus one who is a decorator (the omitted category). Likewise, f , the coefficient of "medium income," is the estimated difference in usage between a person who reports having medium income versus one who has high income. (It is irrelevant which category is dropped, as the estimated differences would be the same even though the coefficients themselves would change.)

Suppose we obtained the following results in which all coefficients are statistically significant:

$$\begin{aligned} \text{Usage} = & 10.3 + 2.1 \times \text{CO} - 1.9 \times \text{EC} - 3.5 \times \text{DI} \\ & - 2.5 \times \text{LOWY} - 1.1 \times \text{MEDY} + 0.9 \times \text{FAMSIZE}. \end{aligned}$$

What would be the market segmentation implications? In this case, convenience-oriented cooks have the highest usage rate: 2.1 units more, on average, than the omitted category, decorators. Both of the other categories of cooking attitude use less than decorators, as the negative signs on their coefficients indicate. In terms of income, high-income consumers are estimated to have the highest usage rate (both signs on the other

income variables are negative). Finally, for every one-person increase in family size, reported usage increases an estimated .9 units (i.e., cans). Thus, the profile of the largest cranberry sauce users is (hypothetically) high-income, convenience-oriented cooks with large families.

One statistic produced with regression equations is R^2 , which measures the degree to which the equation "fits" the data on a 0 to 1 scale, with 1 being a perfect fit. Unfortunately, for frequently purchased products, these kinds of equations tend to have low R^2 values. However, despite the poor fits, these regressions often point to useful bases for segmentation. Figure 6-21 shows that large and significant differences in product consumption can exist even when the R^2 values are low.

Latent Class Analysis. The previous methods begin with individual customers and then aggregate them. Latent class methods, by contrast, begin with the market as a whole and then determine what segmentation pattern best trades off parsimony (few segments) and the ability to explain overall behavior based on derived segments in which all customers in a segment behave identically. This relatively recent approach (see Appendix 6B) is intriguing but requires considerable sophistication, and so it is not yet widely employed. (What this means is you can either (1) ignore it, (2) use it for competitive advantage, or (3) drop the term in conversation to either impress or mystify others.)

A simple kind of latent structure analysis focuses on brand switching data. However, rather than estimating share at the individual level and then grouping similar individuals together (e.g., via cluster analysis), this method simply derives segment-level probabilities and market shares. Grover and Srinivasan (1987) provide an example of such segmentation for the instant coffee market. Subjects who always bought the same brand were classified as loyal while the rest (switchers) were then broken into various segments. Figure 6-22 shows the four-segment solution, which appeared to be the best compromise between explanation and parsimony. The results suggest very small hard-core loyal segments (which in total account for 35 percent of the market) and four switching segments with tendencies to favor two or more brands.

Kamakura and Russell (1989) extend this approach to include price sensitivity. They analyze 78 weeks of purchases of a refrigerated (once opened) food product with a 10-week average purchase cycle. The four brands (A, B, C, P) were average priced at \$4.29, \$3.54, \$3.38, and \$3.09 and had choice shares of 35.8, 27.8, 23.8, and 12.6 percent, respectively. The resulting segments appear in Figure 6-23. Interestingly, these results also suggest that about one-third (31.4 percent) of the customers are hard-core loyal. In addition, the segments differ in terms of price sensitivity. Segments one and two (which account for 19 percent of the market) appear to be relatively insensitive to price and fairly brand loyal. By contrast, segments three and four (which account for 42.2 percent of the market) are quite price sensitive and tend to spread purchases across several brands. Segment five appears not to respond to price or be very brand loyal; perhaps this small (7.4 percent) segment represents customers for whom the product is low involvement and who simply pick a brand by reaching for the most readily available one.

Judgment-Based Segmentation. There is a strong tendency to derive segments by examining data. Still, some of the most useful segmentation schemes are simply descriptors on

FIGURE 6-21 Light and Heavy Buyers by Mean Purchase Rates for Different Socioeconomic Cells

R^2	Product	Description	Mean Consumption Rate Ranges		Ratio of Highest to Lowest Rate
			Light Buyers	Heavy Buyers	
.08	Catsup	Unmarried or married over age 50 without children	.74-1.82	2.73-5.79	7.8
.07	Frozen orange juice	Under 35 or over 65, income less than \$10,000, not college grads, two or less children	1.12-2.24	3.53-9.00	8.0
.04	Pancake mix	Some college, two or less children	.48-.52	1.10-1.51	3.3
.08	Candy bars	Under 35, no children	1.01-4.31	6.65-22.29	21.9
.08	Cake mix	Not married or under 35, no children, income under \$10,000, TV less than 3½ hours	.55-1.10	2.22-3.80	6.9
.09	Beer	Under 25 or over 50, college education, nonprofessional, TV less than 2 hours	0-12.33	17.26-40.30	—
.02	Cream shampoo	Income less than \$8,000, at least some college, less than five children	.16-.35	.44-.87	5.5
.06	Hair spray	Over 65, under \$8,000 income	0-.41	.52-1.68	—
.09	Toothpaste	Over 50, less than three children, income less than \$8,000	1.41-2.01	2.22-4.39	3.1
.03	Mouthwash	Under 35 or over 65, less than \$8,000 income, some college	.46-.85	.98-1.17	2.5

Source: Frank Bass, Douglas Tigerts, and Ronald Lonsdale, "Market Segmentation—Group versus Individual Behavior," Reprinted from *Journal of Marketing Research* 5, published by the American Marketing Association, (August 1968), p. 267.

FIGURE 6-22 Four-Segment Solution for the Instant-Coffee Market

	Brand ^{a,b,c}	Manufacturer ^d	Aggregate Market Share (MS)	Loyal Segment Size	Switching Segments			
					1	2	3	4
					.19*	Size (total = .65) .22*	.18*	.06*
					Within-Segment Market Shares (p) ^e			
HP	D	R	.13	.05*	.09*	.20*	.13*	.08
TC	C	FD	.10	.04*	.07	.03	.18*	.03
TC	D	FD	.07	.01	<u>.1</u>	—	.32*	.12*
FL	C	R	.12	.04*	.20*	.16*	.04*	—
MH	C	R	.21	.08*	.42*	.15*	.07*	.06
S	D	R	.16	.07*	.04*	.22*	.11*	.15*
S	D	FD	.03	.01*	—	.05*	.03*	—
MX	C	FD	.04	.01*	.04*	.03*	.04*	—
N	C	R	.06	.01*	.14*	—	—	.27*
N	D	R	.03	.01	—	.07*	—	.27*
B	D	FD	.05	.02*	—	.09*	.08*	.02
Total			1.00	.35	1.00	1.00	1.00	1.00

*Parameter estimate/standard error > 2.

^aBrand names: HP = High Point; TC = Taster's Choice, FL = Folgers, MH = Maxwell House, S = Sanka, MX = Nescafé, B = Brim.^bD = decaffeinated, C = caffeinated.^cFD = freeze dried, R = regular (spray dried).^dPG = Procter & Gamble, GF = General Foods, N = Nestlé.^eUnderlined numbers denote the two largest choice probabilities within the segment. Probabilities constrained to zero for model identification.Source: Rajiv Grover and V. Srinivasan, "A Simultaneous Approach to Market Segmentation and Market Structuring," *Journal of Marketing Research* 24 (May 1987), p. 147.

FIGURE 6-23 Preference Segmentation and Price Sensitivity

	Loyal Segments				Switching Segments*				
	A	B	C	P	1	2	3	4	5
Choice probabilities									
A	1				.790	.219	.152	.095	.192
B		1			.089	.646	.259	.238	.332
C			1		.069	.092	.520	.301	.133
P				1	.052	.043	.065	.367	.343
Segment size (% of all households)									
	19.0	5.8	3.9	2.7	9.3	9.7	25.8	16.4	7.4
Price sensitivity									
β					-1.87	-1.44	-3.07	-5.42	.37†

*For switching segments 1 through 4, purchase probabilities greater than .10 are underlined.

†Price coefficient statistically insignificant at the .05 level.

Source: Wagner A. Kamakura and Gary J. Russell, "A Probabilistic Choice Model for Market Segmentation and Elasticity Structure," *Journal of Marketing Research* 26 November 1989), p. 385.

bases selected by managers such as customer usage rate (heavy users, light users, nonusers) or product preference. While these are not elegant and are unlikely to suggest a new approach, they are often more useful than so-called natural clusters because the segments are readily identifiable and reachable and obviously have responded differently to the product offering. In fact, it is always advisable to use such a segmentation strategy as at least a basis for comparison with the results of more "data mining" oriented approaches.

No simple way exists to tell how to get the best segmentation scheme. In that respect it's a lot like art—you can tell whether you like it or not but never prove it's the best. The problem when segmenting based on intuition, of course, is that given faulty memory and perceptions, it may produce segments for a market that exist only in the mind of a manager.

Summary. The approaches discussed here can be applied to any product, consumer or industrial, low-tech or high-tech, as long as the required data are available. Many other methods have been used for segmentation. Two methods discussed earlier in this chapter, conjoint analysis and multidimensional scaling, are good examples. In addition, other multivariate techniques (e.g., analysis of variance, logit/probit, Automatic Interaction Detector, and CHAID) can be applied to obtain information about existing market segments.

Illustrations

Super-Premium Ice Cream

Who the Customers Are. Ice cream use in general is widespread. Figure 6-24 presents data from Mediamark Research, Inc.'s 1997 report, and Figure 6-25 provides data based on A.C. Nielsen's home-based scanner panel. Consumption is driven largely by

FIGURE 6-24 Ice Cream Consumption

Base: Female Homemakers	Pints/Last 7 Days																
	All				Heavy More Than 3				Medium 2-3				Light Less Than 2				
	Total U.S. 000	A 000	B %	C %	D Index	A 000	B %	C %	D Index	A 000	B %	C %	D Index	A 000	B %	C %	D Index
All Female Homemakers	89443	63633	100.0	71.1	100	14231	100.0	15.9	100	15422	100.0	17.2	100	33980	100.0	38.0	100
Men	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
Women	89443	63633	100.0	71.1	100	14231	100.0	15.9	100	15422	100.0	17.2	100	33980	100.0	38.0	100
Household Heads	38147	25144	39.5	65.9	93	4545	31.9	11.9	75	5790	37.5	15.2	88	14809	43.6	38.8	102
Homemakers	89443	63633	100.0	71.1	100	14231	100.0	15.9	100	15422	100.0	17.2	100	33980	100.0	38.0	100
Graduated College	17169	12670	19.9	73.8	104	2396	16.8	14.0	88	3268	21.2	19.0	110	7006	20.6	40.8	107
Attended College	23736	17064	26.8	71.9	101	3704	26.0	15.6	98	3585	23.2	15.1	88	9775	28.8	41.2	108
Graduated High School	31977	22813	35.9	71.3	100	5660	39.8	17.7	111	5866	38.0	18.3	106	11287	33.2	35.3	93
Did not Graduate High School	16562	11086	17.4	66.9	94	2470	17.4	14.9	94	2703	17.5	16.3	95	5913	17.4	35.7	94
18-24	7845	4956	7.8	63.2	89	662	4.7	8.4	53	1250	8.1	15.9	92	3044	9.0	38.8	102
25-34	19184	13863	21.8	72.3	102	2533	17.8	13.2	83	3215	20.8	16.8	97	8114	23.9	42.3	111
35-44	20154	15567	24.5	77.2	109	4080	28.7	20.2	127	3386	22.0	16.8	97	8101	23.8	40.2	106
45-54	14824	10377	16.3	70.0	98	2774	19.5	18.7	118	2792	18.1	18.8	109	4811	14.2	32.5	85
55-64	10381	7455	11.7	71.8	101	1677	11.8	16.2	102	2181	14.1	21.0	122	3597	10.6	34.7	91
65 or over	17055	11414	17.9	66.9	94	2505	17.6	14.7	92	2598	16.8	15.2	88	6312	18.6	37.0	97
18-34	27029	18819	29.6	69.6	98	3195	22.5	11.8	74	4465	29.0	16.5	96	11158	32.8	41.3	109
18-49	55545	40303	63.3	72.6	102	9012	63.3	16.2	102	9483	61.5	17.1	99	21807	64.2	39.3	103
25-54	54163	39807	62.6	73.5	103	9387	66.0	17.3	109	9393	60.9	17.3	101	21027	61.9	38.8	102
Employed Full Time	40050	28442	44.7	71.0	100	5795	40.7	14.5	91	6561	42.5	16.4	95	16085	47.3	40.2	106
Part-time	10670	8109	12.7	76.0	107	1721	12.1	16.1	101	2360	15.3	22.1	128	4029	11.9	37.8	99
Sole Wage Earner	13368	8761	13.8	65.5	92	1517	10.7	11.3	71	2074	13.4	15.5	90	5171	15.2	38.7	102
Not Employed	38723	27082	42.6	69.9	98	6714	47.2	17.3	109	6501	42.2	16.8	97	13866	40.8	35.8	94
Professional	9157	6490	10.2	70.9	100	1152	8.1	12.6	79	1578	10.2	17.2	100	3760	11.1	41.1	108
Executive/Admin./Managerial	6777	4981	7.8	73.5	103	1078	7.6	15.9	100	1153	7.5	17.0	99	2750	8.1	40.6	101
Clerical/Sales/Technical	20244	14644	23.0	72.3	102	2880	20.2	14.2	89	3583	23.2	17.7	103	8180	24.1	40.4	106
Precision/Crafts/Repair	1058	709	1.1	67.0	94	*103	0.7	9.7	61	*207	1.3	19.5	113	*400	1.2	37.8	98
Other Employed	13484	9727	15.3	72.1	101	2303	16.2	17.1	107	2400	15.6	17.8	103	5024	14.8	37.3	99
H/D Income \$75,000 or More	13615	10069	15.8	73.9	104	2387	16.8	17.5	110	2326	15.1	17.1	99	5355	15.8	39.3	104
\$60,000-74,999	8572	6519	10.2	76.0	107	1410	9.9	16.4	103	1409	9.1	16.4	95	3700	10.9	43.2	114
\$50,000-59,999	7341	5447	8.6	74.2	104	990	7.0	13.5	85	1286	8.3	17.5	102	3171	9.3	43.2	114
\$40,000-49,999	9283	6695	10.5	72.1	101	1358	9.5	14.6	92	1701	11.0	18.3	106	3636	10.7	39.2	103
\$30,000-39,999	11776	8296	13.0	70.5	99	1801	12.7	15.3	96	2164	14.0	18.4	107	4331	12.7	36.8	97
\$20,000-29,999	13159	9596	15.1	72.9	103	2635	18.5	20.0	126	2210	14.3	16.8	107	4751	14.0	36.1	95
\$10,000-19,999	14645	9923	15.6	67.8	95	2326	16.3	15.9	100	2712	17.6	18.5	107	4886	14.4	33.4	88
Less than \$10,999	11051	7088	11.1	64.1	90	1323	9.3	12.0	75	1613	10.5	14.6	85	4151	12.2	37.6	99

Census Region: North East	17920	13518	21.2	75.4	106	3020	21.2	16.9	106	3454	22.4	19.3	112	7044	20.7	39.3	103
North Central	20997	16295	25.6	77.6	109	3912	27.5	18.6	117	3945	25.6	18.8	109	8438	24.8	40.2	106
South	32866	20803	32.7	63.3	89	4555	32.0	13.9	87	5265	34.1	16.0	93	10982	32.3	33.4	88
West	17660	13017	20.5	73.7	104	2744	19.3	15.5	98	2758	17.9	15.6	91	7515	22.1	42.6	112
Marketing Reg.: New England	4683	3585	5.6	76.6	108	787	5.5	16.8	106	1013	6.6	21.6	125	1784	5.3	38.1	100
Middle Atlantic	15091	11018	17.3	73.0	103	2395	16.8	15.9	100	2694	17.5	17.9	104	5930	17.5	39.3	103
East Central	12106	9334	14.7	77.1	108	2225	15.6	18.4	115	2200	14.3	18.2	105	4910	14.4	40.6	107
West Central	13576	10326	16.2	76.1	107	2692	18.9	19.8	125	2296	14.9	16.9	98	5337	15.7	39.3	103
South East	18186	10686	16.8	58.8	83	1833	12.9	10.1	63	2909	18.9	16.0	93	5943	17.5	32.7	86
South West	10325	7291	11.5	70.6	99	1929	13.6	18.7	117	1791	11.6	17.3	101	3570	10.5	34.6	91
Pacific	15477	11393	17.9	73.6	103	2369	16.6	15.3	96	2518	16.3	16.3	94	6506	19.1	42.0	111
County Size A	35180	25404	39.9	72.2	102	5123	36.0	14.6	92	6278	40.7	17.8	103	14004	41.2	39.8	105
County Size B	27427	19062	30.0	69.5	98	4318	30.3	15.7	99	4637	30.1	16.9	98	10106	29.7	36.8	97
County Size C	12976	8818	13.9	68.0	96	1946	13.7	15.0	94	1946	12.6	15.0	87	4927	14.5	38.0	100
County Size D	13861	10348	16.3	74.7	105	2843	20.0	20.5	129	2562	16.6	18.5	107	4943	14.5	35.7	94
MSA Central City	30121	20703	32.5	68.7	97	4401	30.9	14.6	92	4657	30.2	15.5	90	11645	34.3	38.7	102
MSA Suburban	40932	29522	46.4	72.1	101	6315	44.4	15.4	97	7565	49.1	18.5	101	15641	46.0	38.2	101
Non-MSA	18391	13408	21.1	72.9	102	3514	24.7	19.1	120	3200	20.7	17.4	101	6694	19.7	36.4	96
Single	13825	8991	14.1	65.0	91	1536	10.8	11.1	70	1786	11.6	12.9	75	5668	16.7	41.0	108
Married	52777	39574	62.2	75.0	105	9875	69.4	18.7	118	9822	63.7	18.6	108	19877	58.5	37.7	99
Other	22842	15068	23.7	66.0	93	2820	19.8	12.3	78	3814	24.7	16.7	97	8434	24.8	36.9	97
Parents	36556	27963	43.9	76.5	108	6832	48.0	18.7	117	6935	45.0	19.0	110	14197	41.8	38.8	102
Working Parents	24493	18794	29.5	76.7	108	4346	30.5	17.7	112	4541	29.4	18.5	108	9908	29.2	40.5	106
Household Size: 1 Person	14703	8864	13.9	60.3	85	1342	9.4	9.1	57	1845	12.0	12.5	73	5677	16.7	38.6	102
2 Persons	28180	19810	31.1	70.3	99	4096	28.8	14.5	91	5028	32.6	17.8	103	10887	31.4	37.9	100
3 or More	46561	34958	54.9	75.1	106	8793	61.8	18.9	119	8549	55.4	18.4	106	17616	51.8	37.8	100
Any Child in Household	40040	30625	48.1	76.5	108	7459	52.4	18.6	117	7629	49.5	19.1	111	15537	45.7	38.8	102
Under 2 Years	7574	5936	9.3	78.4	110	920	6.5	12.1	76	1421	9.2	18.8	109	3595	10.6	47.5	125
2-5 Years	16305	12340	19.4	75.7	106	2728	19.2	16.7	105	2968	19.2	18.2	106	6644	19.6	40.7	107
6-11 Years	18883	14756	23.2	78.1	110	4080	28.7	21.6	136	3581	23.2	19.0	110	7096	20.9	37.6	99
12-17 Years	16883	13418	21.1	79.5	112	3912	27.5	23.2	146	3298	21.4	19.5	113	6208	18.3	36.8	97
White	76161	55072	86.5	72.3	102	12339	86.7	16.2	102	13372	86.7	17.6	102	29362	86.4	38.6	101
Black	10317	6164	9.7	59.7	84	1338	9.4	13.0	81	1590	10.3	15.4	89	3236	9.5	31.4	83
Spanish Speaking	7447	5355	8.4	71.9	101	1275	9.0	17.1	108	1435	9.3	19.3	112	2646	7.8	35.5	94
Home Owned	60417	44454	69.9	73.6	103	10511	73.9	17.4	109	10949	71.0	18.1	105	22993	67.7	38.1	100

Source: Mediamark Research, Inc., 1997.

FIGURE 6-25 Ice Cream Consumption

	<i>Ice Cream—Bulk</i>	<i>Ice Milk and Sherbet</i>	<i>Frozen Yogurt</i>
Penetration	87.1	24.7	26.2
Purchase cycle (days)	27.0	46.0	33.0
% \$ on Deal	37.3	23.3	32.8
% \$ Manufacturer coupons	3.5	1.4	4.4
% Repeat buyer	8.8	44.0	51.0
% by Store Type			
Food outlet	97.9	98.9	98.9
Drug outlet	2.0	1.1	1.1
Age of Head of Household			
< 35	89	78	65
35–44	103	106	74
45–54	102	88	106
55–64	108	118	141
65 +	100	118	135
Household Size			
1	64	72	102
2	107	120	128
3–4	108	101	82
5 +	142	106	64
Children Under 18			
None	91	100	118
Any under 18	116	99	68
Any under 6	106	83	65
Any 6–12	121	108	58
Any 13–17	129	108	77
Household Income			
< 12,000	82	85	88
12,000–19,000	87	97	83
20,000–29,000	96	98	90
30,000–39,000	101	97	97
40,000–49,000	108	105	92
50,000–59,000	106	85	118
60,000 +	115	120	127
Occupation of Head of Household			
Professional / mgr.	97	100	100
Clerical / sales	93	97	106
Blue collar	104	85	70
Not in workforce	102	112	122
Household Lifestyle			
Young single	49	35	57
Childless young couple	80	75	91
New family	94	64	83
Maturing family	121	107	56
Established family	119	103	90
Middle-aged single	58	53	92
Childless couple	102	116	92
Aged empty-nester	120	133	158
Older single	72	94	120
Race			
Caucasian	103	104	110
African-American	81	85	59
Asian	77	65	37
Hispanic	102	114	80

Source: Consumer Dimensions 2000, A. C. Nielsen Homescan Panel, 1997.

stage in life cycle and income: High income families with larger families consume more. There is also some evidence that, in the United States, whites and Hispanics consume more than African-Americans or Asians.

Focusing on super-premium ice cream, we see (Figure 6-26) evidence that consumption is highest in the young, upscale, college-educated market, both in general and in comparison to Dreyers' current customers, although 20 percent of households buy super-premium at least once a year. Interestingly consumers are predominantly (67 percent) male.

What They Buy

- *Sales by category:* Super-Premium 10.1%
Premium 45.0%
Regular 20.1%
Private Label 23.7%
- *Sales by Flavor:* A large number of flavors are consumed with vanilla (29.0 percent) and chocolate (8.9 percent) the top two choices (see Figure 6-27). Dreyers' top 10 flavors in 1999 are shown in Figure 6-28.
- *Sales by Brand:* Data based on IRI's *Marketing Fact Book* for 1997 show supermarket sales by brand as well as price paid and dealing activity (Figure 6-29).

When They Buy. Consumption is related to temperature (and therefore seasonal). For example, using data from the early 1950s, a regression of consumption over four weeks versus temperature showed ($R^2 = 60\%$): per capita consumption in pints = $.21 + .0031$ (temperature).

Where They Buy. In general, since 1992 more food has been purchased at restaurants than at supermarkets. The two main sources of super-premium ice cream sales are on-premise outlets and supermarkets.

The top five cities in sales of ice cream per capita in 1999 were Portland, Baltimore, Omaha, Buffalo/Rochester, and Seattle, while New York and Los Angeles led in total consumption. More generally, the Northeast and West are heavy consumption areas.

FIGURE 6-26 Ice Cream Sales by Brand

	TOTAL U.S. 000	Edy's Grand				Häagen Dazs				Breyers				Dreyer's Grand				Ben & Jerry's			
		A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D
Base: Female Homemakers	000	000	% Down	% Across	Index	000	% Down	% Across	Index	000	% Down	% Across	Index	000	% Down	% Across	Index	000	% Down	% Across	Index
All Female Homemakers	89443	4703	100.0	5.3	100	6157	100.0	6.9	100	14713	100.0	16.4	100	2889	100.0	3.2	100	5918	100.0	6.6	100
Men	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
Women	89443	4703	100.0	5.3	100	6157	100.0	6.9	100	14713	100.0	16.4	100	2889	100.0	3.2	100	5918	100.0	6.6	100
Household Heads	38147	1575	33.5	4.1	79	2563	41.6	6.7	98	5806	39.5	15.2	93	1269	43.9	3.3	103	2380	40.2	6.2	94
Homemakers	89443	4703	100.0	5.3	100	6157	100.0	6.9	100	14713	100.0	16.4	100	2889	100.0	3.2	100	5918	100.0	6.6	100
Graduated College	17169	1285	27.3	7.5	142	2160	35.1	12.6	183	3730	25.4	21.7	132	1047	36.2	6.1	189	2016	34.1	11.7	177
Attended College	23736	1366	29.0	5.8	109	1789	29.1	7.5	110	4265	29.0	18.0	109	858	29.7	3.6	112	2027	34.3	8.5	129
Graduated High School	31977	1588	33.8	5.0	94	1656	26.9	5.2	75	4692	31.9	14.7	89	732	25.3	2.3	71	1352	22.8	4.2	64
Did not Graduate High School	16562	*463	9.9	2.8	53	552	9.0	3.3	48	2024	13.8	12.2	74	*251	8.7	1.5	47	523	8.8	3.2	48
18-24	7845	*399	8.5	5.1	97	779	12.7	9.9	144	1226	8.3	15.6	95	*280	9.7	3.6	110	893	15.1	11.4	172
25-34	19184	799	17.0	4.2	79	1654	26.9	8.6	125	3579	24.3	18.7	113	715	24.8	3.7	115	1618	27.3	8.4	127
35-44	20154	1358	28.9	6.7	128	1524	24.8	7.6	110	3991	27.1	19.8	120	575	19.9	2.9	88	1743	29.4	8.6	131
45-54	14824	764	16.2	5.2	98	927	15.1	6.3	91	2259	15.4	15.2	93	510	17.6	3.4	106	964	16.3	6.5	98
55-64	10381	580	12.3	5.6	106	639	10.4	6.2	89	1418	9.6	13.7	83	*346	12.0	3.3	103	358	6.1	3.5	52
65 or over	17055	803	17.1	4.7	90	634	10.3	3.7	54	2239	15.2	13.1	80	464	16.0	2.7	84	342	5.8	2.0	30
18-34	27029	1196	25.5	4.4	84	2433	39.5	9.0	131	4806	32.7	17.8	108	995	34.4	3.7	114	2511	42.4	9.3	140
18-49	55545	2960	62.9	5.3	101	4441	72.1	8.0	116	10070	68.4	18.1	110	1888	65.4	3.4	105	4789	80.9	8.6	130
25-54	54163	2921	62.1	5.4	103	4105	66.7	7.6	110	9829	66.8	18.1	110	1800	62.3	3.3	103	4325	73.1	8.0	121
Employed Full Time	40050	2197	46.7	5.5	104	3285	53.4	8.2	119	6743	45.8	16.8	102	1400	48.5	3.5	108	3462	58.5	8.6	131
Part-time	10670	697	14.8	6.5	124	699	11.4	6.6	95	1969	13.4	18.5	112	*377	13.0	3.5	109	809	13.7	7.6	115
Sole Wage Earner	13368	544	11.6	4.1	77	993	16.1	7.4	108	1721	11.7	12.9	78	302	10.4	2.3	70	1070	18.1	8.0	121
Not Employed	38723	1810	38.5	4.7	89	2173	35.3	5.6	82	6000	40.8	15.5	94	1112	38.5	2.9	89	1647	27.8	4.3	64
Professional	9157	770	16.4	8.4	160	923	15.2	10.2	148	1916	13.0	20.9	127	*338	11.7	3.7	114	860	14.5	9.4	142
Executive/Admin./Managerial	6777	*429	9.1	6.3	120	787	12.8	11.6	169	1410	9.6	20.8	127	*255	8.8	3.8	116	900	15.2	13.3	201
Clerical/Sales/Technical	20244	1104	23.5	5.5	104	1515	24.6	7.5	109	3270	22.2	16.2	98	722	25.0	3.6	110	1692	28.6	8.4	126
Precision/Crafts/Repair	1058	*11	0.2	1.0	19	*45	0.7	4.2	61	*203	1.4	19.2	117	*106	3.7	10.0	310	*34	0.6	3.2	48
Other Employed	13484	580	12.3	4.3	82	705	11.4	5.2	76	1913	13.0	14.2	86	*356	12.3	2.6	82	786	13.3	5.8	88
H/D Income \$75,000 or More	13615	1129	24.0	8.3	158	1348	21.9	9.9	144	2903	19.7	21.3	130	718	24.9	5.3	163	1522	25.7	11.2	169
\$60,000 - 74,999	8572	694	14.8	8.1	154	926	15.0	10.8	157	2068	14.1	24.1	147	*339	11.7	3.9	122	775	13.1	9.0	137
\$50,000 - 59,999	7341	482	10.3	6.6	125	463	7.5	6.3	92	1373	9.3	18.7	114	*249	8.6	3.4	105	615	10.4	8.4	127
\$40,000 - 49,999	9283	549	11.7	5.9	112	766	12.4	8.3	120	1551	10.5	16.7	102	*313	10.8	3.4	104	715	12.1	7.7	116
\$30,000 - 39,999	11776	529	11.3	4.5	85	597	9.7	5.1	74	1781	12.1	15.1	92	464	16.1	3.9	122	825	13.9	7.0	106
\$20,000 - 29,999	13159	537	11.4	4.1	78	855	13.9	6.5	94	2004	13.6	15.2	93	*307	10.6	2.3	72	614	10.4	4.7	70
\$10,000 - 19,999	14645	*322	6.8	2.2	42	710	11.5	4.9	70	1580	10.7	10.8	66	*302	10.5	2.1	64	518	8.8	3.5	53
Less than \$10,000	11051	461	9.8	4.2	79	491	8.0	4.4	65	1453	9.9	13.1	80	*197	6.8	1.8	55	*333	5.6	3.0	45
Census Region: North East	17920	1532	32.6	8.5	163	2114	34.3	11.8	171	4508	30.6	25.2	153	*58	2.0	0.3	10	1865	31.5	10.4	157
North Central	20997	2011	42.7	9.6	182	960	15.6	4.6	66	3258	22.1	15.5	94	*22	0.8	0.1	3	918	15.5	4.4	66
South	32866	1120	23.8	3.4	65	1393	22.6	4.2	62	4581	31.1	13.9	85	*247	8.5	0.8	23	1167	19.7	3.6	54
West	17660	*41	0.9	0.2	4	1690	27.4	9.6	139	2367	16.1	13.4	81	2563	88.7	14.5	449	1968	33.3	11.1	168
Marketing Reg.: New England	4683	355	7.5	7.6	144	334	5.4	7.1	104	840	5.7	17.9	109	*10	0.3	0.2	6	643	10.9	13.7	208
Middle Atlantic	15091	1318	28.0	8.7	166	1866	30.3	12.4	180	4056	27.6	26.9	163	*48	1.7	0.3	10	1357	22.9	9.0	136
East Central	12106	964	20.5	8.0	151	*291	4.7	2.4	35	1787	12.1	14.8	90	—	—	—	—	470	7.9	3.9	59
West Central	13576	1110	23.6	8.2	156	916	14.9	6.7	98	2109	14.3	15.5	94	*175	6.1	1.3	40	714	12.1	5.3	79
South East	18186	843	17.9	4.6	88	802	13.0	4.4	64	2945	20.0	16.2	98	*76	2.6	0.4	13	627	10.6	3.4	52
South West	10325	*73	1.5	0.7	13	498	8.1	4.8	70	1023	7.0	9.9	60	*170	5.9	1.7	51	394	6.7	3.8	58
Pacific	15477	*41	0.9	0.3	5	1449	23.5	9.4	136	1953	13.3	12.6	77	2410	83.4	15.6	482	1713	28.9	11.1	167

FIGURE 6-26 Ice Cream Sales by Brand (Continued)

	TOTAL U.S. 000	Edy's Grand				Häagen Dazs			
		A	B %	C %	D	A	B %	C %	D
Base: Female Homemakers	000	000	Down	Across	Index	000	Down	Across	Index
County Size A	35180	2850	60.6	8.1	154	4095	66.5	11.6	169
County Size B	27427	1166	24.8	4.3	81	1199	19.5	4.4	64
County Size C	12976	*413	8.8	3.2	60	577	9.4	4.4	65
County Size D	13861	*275	5.8	2.0	38	*286	4.6	2.1	30
MSA Central City	30121	1381	29.4	4.6	87	2396	38.9	8.0	116
MSA Suburban	40932	3005	63.9	7.3	140	3359	54.5	8.2	119
Non-MSA	18391	*317	6.7	1.7	33	*403	6.5	2.2	32
Single	13825	763	16.2	5.5	105	1609	26.1	11.6	169
Married	52777	3124	66.4	5.9	113	3503	56.9	6.6	96
Other	22842	817	17.4	3.6	68	1045	17.0	4.6	66
Parents	36556	2096	44.6	5.7	109	2491	40.5	6.8	99
Working Parents	24493	1568	33.3	6.4	122	1693	27.5	6.9	100
Household Size: 1 Person	14703	528	11.2	3.6	68	657	10.7	4.5	65
2 Persons	28180	1523	32.4	5.4	103	2180	35.4	7.7	112
3 or More	46561	2653	56.4	5.7	108	3320	53.9	7.1	104
Any Child in Household	40040	2205	46.9	5.5	105	2717	44.1	6.8	99
Under 2 Years	7574	443	9.4	5.8	111	659	10.7	8.7	126
2-5 Years	16305	839	17.8	5.1	98	1163	18.9	7.1	104
6-11 Years	18883	1020	21.7	5.4	103	1174	19.1	6.2	90
12-17 Years	16883	947	20.1	5.6	107	1048	17.0	6.2	90
White	76161	4102	87.2	5.4	102	4944	80.3	6.5	94
Black	10317	*469	10.0	4.5	87	579	9.4	5.6	82
Spanish Speaking	7447	*237	5.0	3.2	60	673	10.9	9.0	131
Home Owned	60417	3600	76.5	6.0	113	3455	56.1	5.7	83

Source: Mediamark Research, Inc., 1997.

Personal Digital Assistants

Who the Customers Are. The customers for PDAs are primarily upscale mobile professionals. The current general profile of users is predominantly male, analytical and quantitative in nature, well educated, and over 21 years of age.

Mobile professionals, the key target market, can be segmented as in Figure 6-30. These labels do not help the product manager locate these people, of course. However, early adopters of PDAs have a high incidence of purchasing other high-tech consumer products such as personal and laptop computers, home fax machines, cellular phones, and so forth.

What They Buy. Buyers and potential buyers of PDAs seek the following features in decreasing order of importance:

- Small size/light weight.
- PC connectivity.

	Breyers				Dreyer's Grand				Ben & Jerry's			
	A	B %	C %	D	A	B %	C %	D	A	B %	C %	D
	000	Down	Across	Index	000	Down	Across	Index	000	Down	Across	Index
	7084	48.1	20.1	122	1666	57.7	4.7	147	3424	57.9	9.7	147
	4349	29.6	15.9	96	998	34.5	3.6	113	1404	23.7	5.1	77
	2067	14.1	15.9	97	*97	3.4	0.7	23	680	11.5	5.2	79
	1212	8.2	8.7	53	*129	4.5	0.9	29	*410	6.9	3.0	45
	4639	31.5	15.4	94	1172	40.6	3.9	120	1992	33.7	6.6	100
	7823	53.2	19.1	116	1555	53.8	3.8	118	3343	56.5	8.2	123
	2251	15.3	12.2	74	*163	5.6	0.9	27	583	9.9	3.2	48
	2292	15.6	16.6	101	521	18.0	3.8	117	1645	27.8	11.9	180
	9285	63.1	17.6	107	1796	62.2	3.4	105	3226	54.5	6.1	92
	3136	21.3	13.7	83	573	19.8	2.5	78	1047	17.7	4.6	69
	7195	48.9	19.7	120	1170	40.5	3.2	99	2409	40.7	6.6	100
	4758	32.3	19.4	118	835	28.9	3.4	106	1754	29.6	7.2	108
	1959	13.3	13.3	81	382	13.2	2.6	80	801	13.5	5.4	82
	4279	29.1	15.2	92	989	34.2	3.5	109	1885	31.8	6.7	101
	8475	57.6	18.2	111	1518	52.5	3.3	101	3233	54.6	6.9	105
	7593	51.6	19.0	115	1382	47.8	3.5	107	2563	43.3	6.4	97
	1573	10.7	20.8	126	*247	8.5	3.3	101	526	8.9	6.9	105
	3308	22.5	20.3	123	659	22.8	4.0	125	990	16.7	6.1	92
	3641	24.7	19.3	117	624	21.6	3.3	102	1081	18.3	5.7	87
	2917	19.8	17.3	105	567	19.6	3.4	104	1037	17.5	6.1	93
	12602	85.7	16.5	101	2349	81.3	3.1	95	5194	87.8	6.8	103
	1454	9.9	14.1	86	*133	4.6	1.3	40	*326	85.5	3.2	48
	1213	8.2	16.3	99	*373	12.9	5.0	155	*365	6.2	4.9	74
	10311	70.1	17.1	104	2058	71.2	3.4	105	3526	59.6	5.8	88

E-mail communications capability.

Phone/address book.

Appointment book/calendar/alarm.

One-way paging.

PDAs were initially valued primarily as organizers and less as communications devices by current users (Figure 6-31). This implies that two benefit segments are emerging: (1) those who value PDAs solely for their organizer features and (2) a smaller but growing group who value them for communications. According to a *Forrester Brief*, 63 percent of buyers use PDAs both at home and at work, 31 percent for only personal use, and 6 percent solely for work. As communications capabilities improve, this latter group will grow. At the present time, demand drops to essentially zero when the price of a PDA exceeds \$500 and appears to increase steeply as it drops below \$500. Also the Palm operating system still has a greater share than Windows CE.

FIGURE 6-27 Popular Ice Cream Flavors

Flavor	Percent Preference
Vanilla	29.0%
Chocolate	8.9
Butter pecan	5.3
Strawberry	5.3
Neapolitan	4.2
Chocolate chip	3.9
French vanilla	3.8
Cookies and cream	3.6
Vanilla fudge ripple	2.6
Praline pecan	1.7
Cherry	1.6
Chocolate almond	1.6
Coffee	1.9
Rocky road	1.5
Chocolate marshmallow	1.3
All others (each below 1.3%)	23.7%

Source: www.gigaplex.com (2).

FIGURE 6-28 Top Dreyer's Grand Ice Cream Flavors
(based on year-end 1999)

1. Vanilla (including Vanilla Bean and French Vanilla)
2. Rocky Road
3. Mint Chocolate Chips!
4. Cookies 'N Cream
5. Mocha Almond Fudge
6. Cookie Dough
7. Chocolate (including Double Fudge Brownie)
8. Chocolate Chips!
9. Butter Pecan/Almond Praline
10. Real Strawberry

Source: Dreyer's Ice Cream, www.dreyers.com/scoop/main_cold_topten.html, undated.

FIGURE 6-29 What They Buy: Supermarket Ice Cream Purchases by Brand/Brands

Brand	Type Vol. Share	% HH Buying	Volume/ Purchase	Share of Type Requirements	Price/ Unit Volume	% Volume Trade Deals	% Store Features	% Store Display	% Price Reduction	% Manuf. Coupons	% Off Price Deals
Agway/Hood	1.89	3.37	5.23	33.09	0.67	62.59	55.83	11.17	16.57	10.97	21.60
Ben & Jerry's	0.53	6.57	1.38	7.03	2.68	33.78	17.75	7.25	24.82	2.55	27.54
Blue Bell	3.12	6.44	4.38	45.84	0.97	58.79	38.96	12.36	43.90	0.50	29.41
Kemps	3.87	6.29	6.51	35.67	0.55	64.31	36.13	22.46	55.62	2.22	25.83
Healthy Choice	3.02	10.62	3.77	20.44	0.96	48.03	23.58	7.86	41.50	37.31	33.13
Dean's (Mayfield)	3.68	9.03	4.61	28.66	0.74	42.63	27.07	6.32	36.76	5.15	31.04
Dryers	14.29	35.29	4.87	28.63	0.90	69.06	45.14	14.77	50.86	10.40	35.07
Häagen-Dazs	0.93	9.25	1.52	9.74	2.64	39.48	22.14	4.57	32.47	11.94	28.25
Starbucks	0.25	1.99	2.18	10.18	1.93	23.40	7.82	1.93	19.61	8.05	18.41
Friendly's	2.60	6.82	5.66	22.79	0.83	73.66	66.06	15.53	33.00	15.89	35.62
Turkey Hill	2.35	5.84	5.18	25.19	0.76	81.62	69.68	10.56	47.49	9.31	40.40
Breyer's	10.89	31.02	4.76	25.38	0.89	63.56	39.77	11.82	49.02	7.07	31.92
Wells	2.67	5.72	5.52	27.56	0.63	49.50	28.05	6.99	40.56	8.46	26.32
Private Label	36.45	53.79	5.56	51.67	0.53	57.55	33.54	10.20	44.45	0.16	29.20

Average Volume / Household = 36.83

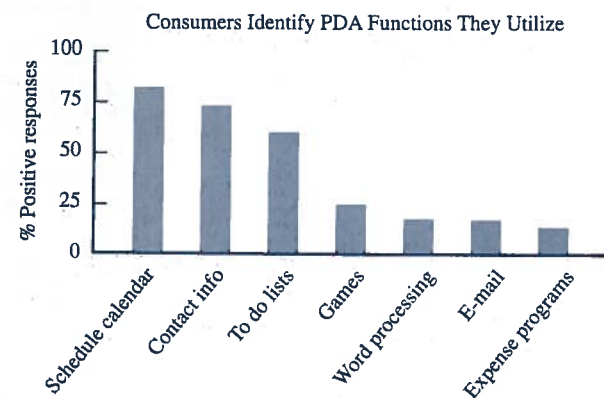
Source: Information Resources Inc., Marketing Fact Book, 1997; Brands greater than 1% share plus Ben and Jerry's, Häagen Dazs, Starbucks.

FIGURE 6-30 PDA Market Segments

Segment	Size	Characteristics	Distinctive Attribute
Wide Area Travelers:			
Globetrotters	10%	Age 45-54; mostly male Employed in senior positions	Innovators, have modems installed in their portable PCs
Road Warriors	20%	Mostly in corporate management and sales, property management and real estate	High cellular phone usage Overall computer usage lower than for other mobile pros
Corporate Wanderers	12%	Travel less than Globetrotters or Road Warriors; spend most time visiting employees within their own companies	Employ portable PCs least Heaviest fax users (on PCs) High e-mail users Longest owners of cellular phones
Local Area Travelers:			
Collaborators	8%	Age 25-44 Well-educated young professionals, tend to hold advanced degrees Team leaders, project managers	Innovators High use of pagers (20% of segment) Not very mobile but need mobile products
Corridor Cruisers	15%	Similar profile to Collaborators	Not as likely to adopt new products as Collaborators
Hermits	8%	Least mobile Youngest segment (many under 35) Seldom work with others	Heavy e-mail users Virtually all are PC users but not portable users
Solo Practitioners	16%	Mostly finance and telemarketing Like Hermits but older Diverse collection of technical professionals in small to medium-size companies	Typically connect to corporate network when traveling Highest connect times of any group
Small-Site Bosses	11%	Run small businesses	Highest portable PC purchase intention in next 12 months; shifting to portable PC as primary computer

FIGURE 6-31

Important PDA functions



Source: Forrester Research Inc., July 1999.

FIGURE 6-32 Motorcycle Segment Lifestyle Descriptors

Segment	Description
Tour Gliders (13.8%)	I like long-distance touring bikes. I use my bike for touring. My bike is made more for comfort than for speed. I love to ride long distances . . . to me, 500 miles is a short trip. I like bikes with plastic fairings and engine covers.
Dream Riders (39.8%)	Most of the time, my motorcycle is just parked. I like wearing a helmet when I ride. I don't know many other people that ride motorcycles. My bike is pretty much stock. I mainly use my bike for short trips around town.
Hard Core (9.7%)	Some people would call me and my friends "outlaws." I have spent lots on speed modifications for my bike. Sometimes I feel like an "outlaw." Some people would call me a "dirty biker." I think it's true that "real men wear black."
Hog Heaven (8.7%)	When I'm on my bike, people seem to be admiring me. I really believe that cars are confining, like a "cage." Women admire my motorcycle. When I ride I feel like an Old Wild West cowboy. I feel close to other motorcyclists I see on the road.
Zen Riders (20.3%)	I like dirt bikes. When I'm on my bike, people seem to be admiring me. I like the attention I get when I'm on my bike. Most of the time, my motorcycle is just parked. I get excited about motocross or scrambling.
Live to Ride (7.6%)	I love to ride long distances . . . to me, 500 miles is a short trip. Motorcycles are a total lifestyle to me. Riding, to me, is often a magical experience. It's true that "I live to ride and ride to live." My bike is everything to me.

Source: William R. Swinyard, "The Hard Core and Zen Riders of Harley Davidson: A Market-Driven Segmentation Analysis," *Journal of Targeting, Measurement and Analysis for Marketing* 4, June 1996, pp. 349-50.

How They Buy. Advertising and marketing have not been key influencers in PDA purchase decisions to this point. Current users sought out the devices themselves. Again, this is not unusual for a product at the early stage of the product life cycle. Later users, however, will rely more on information-based advertising and recommendations from colleagues and friends.

Where They Buy. Customers buy lower-priced, low-feature devices from consumer electronics stores and office supply superstores (e.g., Office Max, Office Depot). Higher-end PDAs are purchased from computer stores or through mail order or via the Internet.

Motorcycles

For those readers who find ice cream and PDAs too tame to be interesting, Figures 6-32 and 6-33 show a segmentation scheme for motorcycle riders.

FIGURE 6-33 Summary of Demographic and Motorcycle Ownership Characteristics, by Segment

	<i>Tour Gliders</i>	<i>Dream Riders</i>	<i>Hard Core</i>	<i>Hog Heaven</i>	<i>Zen Riders</i>	<i>Live to Ride</i>
Demographics						
Average owner age	42.6	42.9	36.2	39.2	36.9	36.6
Sex male	93.8%	95.1%	93.5%	85.4%	94.7%	91.7%
Married	60.0%	68.5%	51.1%	56.1%	75.0%	58.3%
Number of children at home	1.3	1.2	1.0	1.2	1.2	1.2
Education: college graduate	15.4%	24.7%	8.7%	7.3%	19.8%	25.0%
Income of \$50,000 and over . . .						
Personal	29.7%	30.2%	4.4%	31.7%	26.3%	25.0%
Household	50.8%	52.0%	26.6%	41.0%	55.4%	55.5%
Average income:						
Personal	\$40,438	\$40,087	\$27,389	\$34,744	\$38,816	\$33,667
Household	\$46,563	\$46,500	\$34,944	\$40,397	\$47,435	\$44,222
Occupation: Professional/ managerial	21.5%	30.1%	0.0%	26.8%	19.8%	29.4%
Motorcycle Ownership						
Motorcycle is 1991 or newer	24.6%	30.7%	7.3%	22.0%	28.7%	15.2%
Owned motorcycle under 2 years	16.7%	22.7%	10.3%	35.5%	30.4%	30.3%
Brought motorcycle new	40.0%	50.0%	15.2%	45.0%	33.0%	55.9%
Model year of principal Harley	1985.9	1985.8	1980.5	1986.2	1983.6	1985.7
This is their first motorcycle	1.5%	9.0%	15.9%	19.5%	9.4%	2.8%
No. of motorcycles owned	9.06	5.34	6.3	6.82	5.7	9.77
No. of Harleys owned	4.74	1.63	2.85	2.13	1.44	2.12
Money spent on motorcycle for . . .						
Purchase of motorcycle	\$9,048	\$7,460	\$5,082	\$6,631	\$6,966	\$8,976
Parts/accessories this year	\$ 690	\$ 322	\$1,260	\$ 321	\$ 767	\$ 860
Parts/accessories in total	\$1,571	\$1,426	\$3,233	\$2,419	\$1,734	\$2,483
Estimated value of motorcycle today	\$10,066	\$8,414	\$8,062	\$8,591	\$8,827	\$10,342
Riding per year . . .						
Number of miles	7351	3675	7099	5051	4169	9662
Number of days	188	109	187	148	112	214
Number years riding	24.1	20.2	16.5	16.9	18	17.7
Type of motorcycle they ride:						
Touring	39.0%	16.4%	0.0%	7.9%	12.6%	31.3%
Full Dress	18.6%	18.6%	11.4%	10.5%	14.9%	18.9%
Cruiser	23.8%	26.0%	36.4%	29.0%	28.7%	31.3%
Sportster	5.1%	30.5%	29.5%	52.6%	35.6%	0.0%
Other type	13.6%	8.5%	22.7%	0.0%	8.0%	18.8%

Source: William R. Swinyard, "The Hard Core and Zen Riders of Harley Davidson: A Market-Driven Segmentation Analysis," *Journal of Targeting, Measurement and Analysis for Marketing* 4, June 1996, p. 351.

Summary

All phases of customer analysis provide potentially useful information. However, a tremendous amount of this information can be summarized in a figure that includes segments across the top and the various aspects of customer analysis as the rows of the figure to describe the segments.

The process of arriving at a useful version of such a figure is likely to be messy, imprecise, and involve trial and error. The best approach is to try several different schemes for defining the segments (e.g., versions of who or why, possibly in combination). The choice of which segmentation scheme to use often depends on the insight gained and the potential for the segmentation scheme to lead to useful strategies (e.g., selecting which segments to serve) and efficient program (e.g., advertising, distribution) determination.

In analyzing customers, it is both natural and useful to look at history. Nonetheless, the reason for doing so is not to be a good historian, but to be a good forecaster. Put differently, one needs to make judgments about what might cause behavior to change (including both your actions and outside influences such as culture, competition, economic conditions, and regulation). In addition, some assessment is needed of the likelihood these causal influences will in fact change. Finally, the impact of likely changes on customer behavior, and consequently sales, must be analyzed. Then and only then will customer analysis be useful for deciding what to do in the future and what trends to monitor most closely.

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APPENDIX 6A

ECONOMIC VALUE TO THE CUSTOMER (EVC)

Basic Concept

The economic value to the customer is the net dollar value (savings) from using a particular product (often a new one) instead of a relevant substitute (often the one currently used). That is, it is the difference in the total direct cost of using two competing products. Total cost is measured either for a particular time period (e.g., month, year) or activity (job). Since it is frequently used as a means to set price for a new product, it often is computed using the price of the comparison/old product as part of its cost but no price for the new product. At the most general level, the calculation looks like Figure 6A-1 where the difference in Total Costs ($TC_A - TC_N$) is the economic (cash) value of switching from the old to the new product for the time period or activity level used

as a basis of calculation. (For example, if the monthly EVC is \$10,000, then the yearly savings is \$120,000; similarly, if the EVC is \$5,000 per job and the firm completes 40 jobs per year, the yearly EVC is \$200,000.)

Example

A new synthetic motor oil is about to be introduced with the primary benefit that it needs to be changed less frequently, specifically once every two years regardless of mileage. Assume current oils need to be changed every 6,000 miles at a cost of \$30 per change (oil at a dollar a quart or a total of \$5, labor \$20, disposal of oil \$5) for an average car. What is the EVC of the new oil to a driver who drives 15,000 miles per year?

This is a straightforward problem where it is relatively easy to get the EVC for a given mileage. First set up Figure 6A-2 similar to Figure 6A-1. We use a two-year basis because it makes the calculation easy. The key distinction between the old and the new is the number of oil changes needed in the two-year period: 1 for the new product and $(2)(15,000/6,000) = 5$ for the old product.

Therefore the economic value (benefit) to using the new product versus the old is $\$150 - \$25 = \$125$ over the two-year period. Converting this to a per-quart basis means the value of the new oil is $\$125/5 = \25 per quart.

Implications

One of the major implications of an EVC calculation is for setting prices. For example, consider the improved lubricant example of Figure 6A-2. For such an "industrial" product (i.e., one without important functional/performance or psychological benefits), the maximum price the rational

FIGURE 6-A1 Total Cost Comparison

	(New) Product N	Current (old) Product A	EVC for New Product
Product (part) price	?	P_A	
Labor costs			
Related (e.g., parts) costs			
TOTAL COST	TC_N	TC_A	$TC_A - TC_N$

FIGURE 6-A2 Total Cost: Two Years

	New Synthetic Oil	Old Oil
Product price	?	5 changes \times \$5/change = \$25
Labor costs	1 change \times \$20 = \$20	5 changes \times \$20/change = \$100
Other costs (oil disposal)	\$5	5 change \times \$5 = \$25
TOTAL	\$25	\$150

FIGURE 6-A3 The Relation of EVC of Usage Rate

	New Product	Old Product		
		Low Mileage (3,000)	Average Mileage (15,000)	High Mileage (45,000)
Product price	?	1 × \$5 = \$5	\$25	15 × \$5 = \$75
Labor costs	\$20	1 × \$20 = \$20	\$100	15 × \$20 = \$300
Other costs	\$5	1 × \$5 = \$5	\$25	15 × \$5 = \$75
TOTAL COSTS	\$25	\$30	\$150	\$450
EVC		\$5	\$125	\$425
EVC/Quart of new product		\$1	\$5	\$85

average driver would be willing to pay would be \$25 per quart. However at that price drivers have no incentive to switch to the synthetic (i.e., they are indifferent). In order to give them an incentive to switch, therefore, you must pick a price below \$25 (but hopefully above cost). If direct costs are \$8 per quart, one then selects a price between \$8 and \$25. Generally the greater the competition (i.e., number of producers of synthetic oil), the need to quickly capture customers, and available production capacity, the lower the price.

Issues

First, the calculation assumes that customers believe the benefits exist, optimally use the new product, and perform the calculation correctly. One can deal with the calculation aspect by providing it to potential customers (e.g., in ads, sales pitches, etc.). In terms of beliefs, anyone “trained” to change oil frequently will doubt that the synthetic oil can go two years without changing. If they change it more frequently, the EVC drops. Therefore educating customers is a relevant activity so they both believe the claims and use the product correctly.

Second, EVC depends on the usage rate. In this example, heavy users will find the product much more valuable. Consider two drivers, one who drives 3,000 miles per year and one who drives 45,000. The low mileage (3,000 miles) driver needs only one change every two years anyway, while the high mileage driver would need 15. As Figure 6A-3 shows, the low mileage driver should be willing to pay at most \$1 per quart (the same as for regular oil) whereas the high mileage driver might pay up to \$85. The point of this is that economic value to the customer depends on the particular customer in question.

APPENDIX 6B

LATENT CLASS METHODS

Advances in both computer power and methods have made feasible a different approach to segment construction and interpreting. Most methods discussed in the chapter basically attempt to take individuals and aggregate them into segments. By contrast, latent class methods simultane-

ously estimate segment sizes and their behavior. These methods make use of the simple fact that aggregate market behavior is the sum of individual or segment level behavior:

$$\begin{aligned} \text{Total Market Behavior} &= \sum_{\text{segments}} \left(\text{Size of Segment } i \right) \left(\text{Behavior of Segment } i \right) \\ &= \sum_{\text{segments}} W_i B_i \end{aligned}$$

The latent class approach *simultaneously* estimates segment sizes (W_i s) and segment behavior (B_i s). Segment membership is not known in advance (i.e., there is not a high income or nonresponsive-to-promotion segment specified in advance) and individual customers are not assigned to particular segments.

A key issue involves deciding on the number of segments. Basically this decision involves trading off between better describing a market (which allowing for more segments always does since it increases the number of parameters estimated) and keeping only important or “significant” segments. This trade-off is often accomplished with statistical tests on results of allowing for an additional segment (e.g., five versus four segments) or by comparing the abilities of the more and less parsimonious models to forecast behavior of a holdout sample (that is, customers who were not used to estimate the parameters).

When there is enough data to get an estimate of behavior at the individual customer level, latent class methods often incorporate probabilities of segment membership for each customer:

$$\text{Market Behavior} = \sum_{\text{customers}} \sum_{\text{segments}} P_{ij} B_i$$

where P_{ij} = probability person j is a member of segment i .

In interpreting such analyses, it is desirable to describe segments in terms of descriptor variables (demographics, firm characteristics). This can be done separately from the latent class analysis by relating individuals’ estimated probabilities of being in each segment to other characteristics; that is, letting $P_{ij} = f(\text{characteristics of Customer } j)$. This two-step approach then becomes:

$$\text{Step 1: Market Behavior} = \sum_{\text{customers}} \sum_{\text{segments}} P_{ij} B_i$$

$$\text{Step 2: } P_{ij} \sum_{\text{characteristics}} = C_{ji} X_{ji}$$

Occasionally the two steps are combined in a single step:

$$\text{Market Behavior} = \sum_{\text{customers}} \sum_{\text{segments}} \sum_{\text{characteristics}} (C_{ji} X_{ji} B_i)$$

Currently latent class methods have not been widely applied in commercial settings. It is a good bet, however, that their use will increase substantially.