# Review of Marketing Research

# Review of Marketing Research

VOLUME 2

Naresh K. Malhotra

Editor

M.E. Sharpe

Armonk, New York

London, England

Library of Congress ISSN: 1548-6435
ISBN 0-7656-1305-0 (hardcover)

Printed in the United States of America

The paper used in this publication meets the minimum requirements of
American National Standard for Information Sciences
Permanence of Paper for Printed Library Materials,
ANSI Z 39.48-1984.

∞

MV (c) 10 9 8 7 6 5 4 3 2 1

# REVIEW OF MARKETING RESEARCH

EDITOR: NARESH K. MALHOTRA, GEORGIA INSTITUTE OF TECHNOLOGY

# AD HOC REVIEWERS

# CONTENTS

# REVIEW OF MARKETING RESEARCH: SOME REFLECTIONS

## Introduction

Naresh K. Malhotra

### Overview

*Review of Marketing Research*, now in its second volume, is a recent publication covering the important areas of marketing research with a more comprehensive state-of-the-art orientation. The chapters in this publication will review the literature in a particular area, offer a critical commentary, develop an innovative framework, and discuss future developments in addition to containing specific empirical studies. The response to the first volume has been truly gratifying, and we look forward to the impact of the second volume with great anticipation.

### Publication Mission

The purpose of this series is to provide current, comprehensive, state-of-the-art articles in review of marketing research. A wide range of paradigmatic or theoretical substantive agendas are appropriate for this publication. This includes a wide range of theoretical perspectives, paradigms, data (qualitative, survey, experimental, ethnographic, secondary, etc.), and topics related to the study and explanation of marketing-related phenomena. We hope to reflect an eclectic mixture of theory, data, and research methods that is indicative of a publication driven by important theoretical and substantive problems. We seek papers that make important theoretical, substantive, empirical, methodological, measurement, and modeling contributions. Any topic that fits under the broad area of "marketing research" is relevant. In short, our mission is to publish the best reviews in the discipline.

Thus, this publication will bridge the gap left by current marketing research publications. Current marketing research publications such as the *Journal of Marketing Research* (USA), *Journal of Marketing Research Society* (UK), and *International Journal of Research in Marketing* (Europe) publish academic articles with a major constraint on the length. In contrast, *Review of Marketing Research* will publish much longer articles that are not only theoretically rigorous but more expository and also focus on implementing new marketing research concepts and procedures. This will also serve to distinguish the proposed publication from the *Marketing Research* magazine published by the American Marketing Association (AMA).

Articles in *Review of Marketing Research* should address the following issues:

- Critically review the existing literature.
- Summarize what we know about the subject—key findings.

- Present the main theories and frameworks.
- Review and give an exposition of key methodologies.
- Identify the gaps in literature.
- Present empirical studies (for empirical papers only).
- Discuss emerging trends and issues.
- Focus on international developments.
- Suggest directions for future theory development and testing.
- Recommend guidelines for implementing new procedures and concepts.

**Articles in the First Volume**

The inaugural volume exemplified the broad scope of the *Review of Marketing Research.* It contained a diverse set of review articles covering areas such as emotions, beauty, information search, business and marketing strategy, organizational performance, reference scales, and correspondence analysis. These articles were contributed by leading scholars such as Allison R. Johnson and David W. Stewart, Morris B. Holbrook, Lan Xia and Kent B. Monroe, Shelby D. Hunt and Robert M. Morgan, Sundar G. Bharadwaj and Rajan Varadarajan, Stephen L. Vargo and Robert F. Lusch, and Naresh K. Malhotra, Betsy Charles Bartels, and Can Uslay. The second volume continues this emphasis by featuring a broad range of topics contributed by some of the topmost scholars in the discipline.

**Articles in This Volume**

The diverse articles in this volume may all be grouped under the broad umbrella of consumer action. Bagozzi develops a detailed framework for consumer action in terms of automaticity, purposiveness, and self-regulation. He posits that it is plausible to consider consumer action as a dual process consisting of two modes of information processing. One mode of information processing is reflective or deliberate, whereas the second is automatic and preconscious. Both of these modes are initiated by either internal representations of states of affairs or external cues or stimuli. Consumer action is not merely a response to things that happen. Rather, consumer action involves human agency and self-regulation whereby individuals reflect upon how they feel and think and who they are or desire to be, and decide to act or not accordingly. This comprehensive framework not only presents food for thought but also suggests several avenues for future research.

Focusing on one aspect of consumer action, MacInnis, Patrick, and Park provide a review of affective forecasting and misforecasting. Consumer action is influenced by their forecasts of the affective states they predict will arise in the future. However, affective forecasts are often erroneous as they are susceptible to a variety of errors and biases that reduce their accuracy. The authors identify the antecedents and consequences as well as the moderating factors that influence the relationship between these variables. More research on the nature and extent of affective misforecasting is needed.

Another important aspect of consumer action is information search, and the Internet has become a vital source of information. Ratchford, Lee, and Talukdar review the literature related to use of the Internet as a vehicle for information search. Using detailed data on types of Internet sources employed by automobile buyers, they study the determinants of choice of different types of Internet sources, and the substitution patterns between those types and other non-Internet sources. They develop and empirically test a general model of the choice of information sources with encouraging results. One of their key findings is the importance of the manufacturer source that gets the highest average share of time from Internet users, and the manufacturer source appears to be a major producer of price, performance, and reliability information. Consumer search appears to be limited, both in general and on the Internet. The reasons for this limited search are not well understood and call for more research.

Consumers' perceptions also influence their actions. Miller, Malhotra, and King review the categorization literature and develop a categorization-based model of the product evaluation formation process, which assists in the prediction of set membership (i.e., evoked, inert, or inept). Their model encompasses category-based processing as well as piecemeal processing. They empirically test various methodologies with regard to their abilities to predict set membership. The findings suggest that powerful tools exist for the prediction of set membership. Their research provides useful insights into the evaluation formation and set prediction process. The set prediction abilities of the category-based asymmetrical Multidimensional Scaling (MDS) and piecemeal processing conjoint, hybrid conjoint, and self-explicated utility models were very encouraging. Yet, more detailed theories need to be developed to explain the evaluation formation process so that set membership can be better understood and predicted.

Another important aspect of consumer action is adoption and usage. Lam and Parasuraman propose an integrated framework that incorporates a more comprehensive set of various individual-level determinants of technology adoption and usage. By focusing the conceptualization on the determinants at the individual consumer level, this article seeks to provide an in-depth and detailed discussion of their effects. Based on the framework, they develop a set of propositions regarding how these determinants affect adoption and usage directly and indirectly, and how some of these determinants moderate the effects of other determinants on adoption and usage of technological innovations. Such a propositional inventory not only is useful for identifying critical issues worthy of further investigation, but also provides several implications for makers and marketers of technological innovations.

Much marketing effort is expended to influence consumer action. Recently, marketing has come under increased pressure to justify its budgets and activities. Lehmann briefly reviews the reasons behind the pressure. He develops a metrics value chain to capture the various levels of measurement employed. He also reviews evidence for the various links in the chain. There are problems in establishing the links in the metric value chain, and Lehmann offers suggestions for future work in resolving these issues. Much work needs to be done in terms of generating empirical generalizations about the various links in the chain.

Methodologies are needed to understand and predict consumer actions. Oakley, Iacobucci, and Duhachek provide an exposition of hierarchical linear modeling (HLM). They describe the techniques and illustrate the models on a small data set using existing software so that the reader should be able to reproduce the results they present. They also present findings from a larger, real data set to illustrate the substantive insights that may be gleaned from these models. HLM models subsume a number of more familiar models such as ordinary least squares regression, means as outcomes regression, random coefficients regression, and one-way analysis of variance (ANOVA) with random effects. As such HLM models present a more general framework for analyzing data commonly encountered in marketing research.

It is hoped that collectively the chapters in this volume will substantially aid our efforts to understand, model, and predict consumer action and provide fertile areas for future research.

# Review of Marketing Research

CHAPTER 1

# CONSUMER ACTION

## Automaticity, Purposiveness, and Self-Regulation

RICHARD P. BAGOZZI

**Abstract**

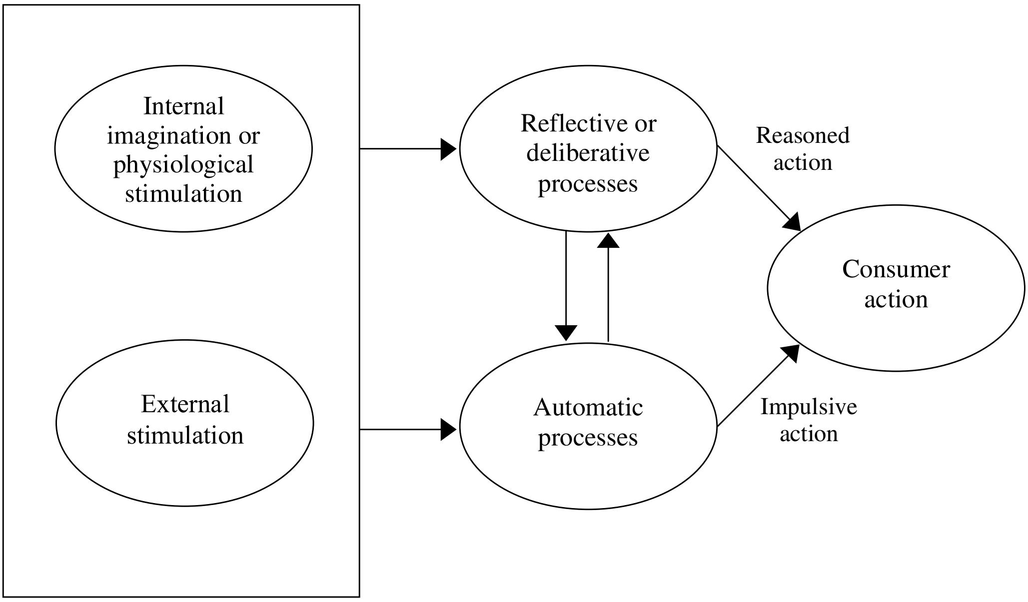
*This chapter investigates the nature and etiology of consumer action with an aim toward specifying the conceptual foundations of consumer action and providing a framework for its study. A dual process theory of consumer action is sketched wherein automatic and deliberative processes are hypothesized to undergird consumer action. In addition to information processing and related cognitive processes, the framework incorporates impulsive, emotional, motivational, volitional, social, and self-regulative elements to describe and account for consumer action. Philosophically, consumer action is taken to be both deterministic and subject to free agency, depending on the nature and history of the consumer and the situations in which consumers find themselves.*

This chapter presents a framework for thinking about consumer action. The framework is rather complex with many variables and processes arranged in a particular way, but the general idea underlying the approach is simple and is summarized in Figure 1.1. Briefly, it is plausible to consider consumer action (defined below) as a dual process consisting of two modes of information processing, both of which are initiated by either internal representations of states of affairs or external cues or stimuli. One mode of information processing is reflective or deliberate; the second is automatic and preconscious. The two modes are connected to each other in ways that will be described below. Although I have been working on major portions of the framework for over a decade and have proposed a number of related integrative expositions of it (e.g., Bagozzi, 1992, 2000a, 2005; Bagozzi, Gürhan-Canli, and Priester, 2002), the presentation herein is more comprehensive, detailed, and unified, and includes a lot of reinterpretation and new thinking as well.

### Brief Reflections on the Field of Consumer Research

Before elaborating the framework, it is useful to provide some perspective drawn from an assessment of the contemporary state of affairs in consumer research. Two issues will be considered: the dominant paradigm and the prevalent method in inquiry.

Figure 1.1 **Outline of Proposed Dual-Process Model of Consumer Action**




### *The Dominant Paradigm*

For more than three decades, the nucleus of consumer research has focused on cognitive processes, information processing, or cognitive responses. Everything else—the study of motivation and emotions, consumer actions, social behavior, and collective consumption phenomena, to name a few—has been at the periphery of inquiry.

The aim of research under the dominant paradigm is to understand how consumers process market-related information (e.g., prices, product attributes and performance, advertising appeals, and store environments). This has led to a wealth of knowledge that might be roughly grouped under such headings as attention processes, perception, memory, information search, categorization, cognitive schemas, judgment and evaluation, inference drawing, and choice.

Much of this research seeks to address antecedents of consumer action or the bases for consumption, but seldom has action ever been investigated as a dependent variable. Rather, in the majority of cases, beliefs, attitudes, or similar *mental* states have been used as the dependent variables to be explained or predicted by the cognitive processes under study. Occasionally, intention is used as a dependent variable but is taken to be a "proxy" for action, assuming the intention-to-action relationship to be nonproblematic. The few attempts to use actual action as a dependent variable have been made without grounding predictions on a well-developed theory of how cognitive responses lead to, result in, or determine action. We have been seduced into thinking that an observed empirical link between a cognitive state or event and an observable action implies that the event causes the action. The observation of bodily movements or outcomes of action all too often serve as the evidence for a causal process without the process being identified per se. Indeed, theoretical and empirical gaps typically exist in research to date between cognitive processes and decisions and between decisions and action (Bagozzi, 1992, 2000a, 2005).

We might identify two superordinate aims of research under the dominant paradigm. One is to describe and understand cognitive processes experienced by consumers as an end for study in and of itself. The second is to provide a basis for predicting, explaining, and, for researchers or practitioners interested in management issues, influencing or controlling consumer action.

Both superordinate aims rest on little understood assumptions and leaps of faith. First, there is the implicit belief that each individual study, each contribution to knowledge, fits into a larger pattern or representation of the total cognitive system. But what the domain and scope of this larger system looks like and what criteria should be used to assess its validity are seldom considered. A pioneering treatise in this regard was done by Bettman (1979), who not only mapped out key mental processes but proposed a novel theory of information processing and decision making that has remarkably stood the test of time. Nevertheless, the many advances of the past 25 years in the cognitive response tradition cry out for updating and perspective-taking worthy of Bettman's tour de force.

Second, and closely related to the above point, we seem to lack guidelines for determining the relative importance of the many cognitive states and processes identified to date. Are all findings concerning information processing equally important and central to our understanding and explanation of consumer behavior? To what extent do such findings duplicate or contradict each other? Have essential processes been neglected for inquiry, including not only cognitive processes but motivational, emotional, social, and others?

Third, what are the conceptual and philosophical foundations upon which contemporary knowledge of consumer behavior rests? Does our knowledge presume a reductionistic outlook? Must group and social phenomena be incorporated through the filter of cognitive processes for us to understand and explain consumer behavior? How do the cognitive processes that have been identified to date relate to physiological processes and what we know from neuroscience? Can cognitive states and processes be represented by what philosophers term *propositional attitudes* (e.g., Goldman, 2000)?[1] What does the dominant paradigm assume or have to say about mental causation (e.g., Bishop, 1989; Heil, 1992; Kim, 2003)? These and other philosophical issues have implications for our theories, measurements, and hypothesis testing but are rarely discussed.

Fourth, how are *consumer* cognitive processes related to more specific and more general cognitive processes? Or are our ideas and knowledge of consumer behavior totally dependent upon or derivative from cognitive science? Consideration of the demarcation between what consumer behavior is and what cognitive psychology, cognitive anthropology, and so on are might lead to identification of understudied areas and what, if anything, is unique to consumer behavior. Such inquiry might lead to a better conceptualization of the field and what constitutes consumer behavior beyond that found in the dominant paradigm.

Finally, an argument can be made for broadening the dominant paradigm to include in its domain volitional and emotive processes. The study of volitional processes seems ripe ground for applying and developing ideas from what we know about information processing and the like to the more conative side of consumer behavior. Similarly, explicit theorizing and research are needed into the linkage between the bases for decision making, which include cognitive processes, and decision making and volition. This would seem to require consideration as well, of other noncognitive content (e.g., motivation, emotion, sociality) under the label of "bases for decision making." Moreover, how and why cognitive and other mental and physiological processes serve to transform volitional processes into action provide important opportunities for future research.

We seem to have arrived at a crossroads in contemporary consumer research. The dominant paradigm has yielded a wealth of knowledge to date, but this knowledge is highly fragmented and the current approach to research is so piecemeal that we risk losing sight of what is central to the understanding of consumer behavior. The proliferation of so many theories and findings in so many subareas of the dominant paradigm is in need of integration and focus. At the same time, unguided, ever deeper inquiry solely into cognitive processes keeps intellectual focus and empirical research from going beyond the cognitive to consider emotional, motivational, and social processes, and especially the phenomenon of consumer action, a topic we will turn to shortly in the section below, entitled Consumer Action.

### *The Prevalent Method in Inquiry*

How new knowledge is unearthed and how hypotheses are tested should not be separated from either the theories upon which the research rests or the interpretation of findings thereof. At least it is important to recognize the intimate relationships among theory, method, observation, and interpretation.

The experimental method, particularly randomized experiments, has been nearly exclusively the procedure of choice by researchers working in the dominant paradigm. This is easy to comprehend when the virtues of experimentation are noted. By randomly assigning people to experimental conditions, defined by specific levels of one or more independent variables, we gain a certain degree of confidence that changes in the dependent variable(s) are caused by the manipulations and not by preexisting differences among the people, such as individual differences, or by differential situational conditions impinging on the groups.

Putting aside the normal threats to validity characteristic of the use of experimentation (see Shadish, Cook, and Campbell, 2001), I feel that it is important to point out boundary conditions with the procedure. By its nature, controlled experimentation tends to be most useful for the investigation of relatively simple phenomena. There are few variables that can be studied in any experiment, and the processes under scrutiny are relatively circumscribed. This is necessary to gain control over contaminating factors. It is often presumed that the causal processes identified in an experiment also occur under conditions outside the laboratory context. Although this may often be true, how and when these processes occur are seldom studied formally, for the conditions under which the causal processes operate in naturalistic circumstances are seldom specified. This issue is related to but different from the question of how all the findings across many experiments in the dominant paradigm articulate to represent consumer behavior from a cognitive perspective.

Another boundary condition of controlled experiments is that it addresses states or processes that occur over relatively short periods of time. It is difficult to study prolonged information processing, processing that entails extended reflection or deliberation, or ongoing and interconnected cognitive responses, with the experimental method.

In short, complex individual and social behavior pose challenges for inquiry by researchers. The experimental method can be used here, but it is important to recognize its limitations in this regard. Exclusive reliance on experimentation risks restricting and even undermining the potential for the field of consumer behavior because how we investigate phenomena shapes its conceptualization and interpretation.

### *A Call for a New Dialogue*

If we are to achieve a true science of consumer behavior, we have to do more than give lip service to the value of pluralism in ideas and approaches in the field. We have different traditions that share and sometimes compete for space in journals, faculties, and the application of knowledge, but there seems to be little learning crossing the boundaries of the various camps. The benefits of pluralism have not spilled over into the theories, findings, and interpretations found in each camp. What seems to be needed are special efforts to span boundaries. This will of necessity mean that the mind-sets and standards of each camp that is bridged must be changed and transformed if true learning is to occur. Means of knowing other than experimentation must also be recognized. In addition to experimentation, knowledge can be gained from survey research, participant observation methods, application of literary principles (e.g., analogical thinking), linguistic analyses, simulations, historical analyses, and other modes of systematic inquiry. Room should be made for research based on what Rozin (2001) terms "informed curiosity," as a complement to model- or hypothesis-driven research. The results of a formal dialogue and openness to different modes of learning can be more insightful theories and more valid findings that enrich the camps involved and the field as a whole.

In this chapter, I attempt to develop a framework that bridges the dominant paradigm and action theory. There are other lacunae to address to be sure, but we have to begin somewhere with pressing issues. I simply suggest herein that not only are theories and findings from the dominant paradigm essential in accounting for decision making targeted at consumer action, but the dominant paradigm can supply needed content to volitional processes and for how these processes influence action. Of course, it will be emphasized that the dominant paradigm needs to be supplemented by ideas from research in emotions and social behavior and that a framework is needed for identifying and linking the concepts and processes in a way that explains consumer action and facilitates its interpretation. The overall framework captures deliberative as well as automatic processes, as determinants of consumer action, to which we now turn.

## Consumer Action

Because we lack a well-defined and commonly accepted conceptualization of consumer action, considerable confusion exists in the literature in this regard. One sense of confusion occurs between the meaning and usage of the terms *consumer behavior* and *consumer action.* I suggest that the psychological processes that consumers undergo be termed *consumer behavior*, so as to differentiate these phenomena from consumer action, which we will define in a moment. It is consumer behavior that researchers primarily study in the tradition of the dominant paradigm, both as independent and dependent variables.

Consumer action has received little conceptual specification in the field and has been used rather loosely and in varied ways. To show the need for a philosophical grounding of consumer action, consider the case of a consumer living in a condominium with three floors, each with its own zoned air conditioning system. The consumer's action with respect to replacing the air conditioning filters might consist of (a) walking down the aisle of a hardware store in search of three filters, (b) reaching for the filters on a shelf and placing them in a shopping cart, (c) making a payment, (d) installing the new filters and disposing of the old, (e) improving the air quality in the home, and (f) adding to the amount of refuge in the environment. Echoing a classic problem raised by philosophers (e.g., Anscombe, 1963, p. 45; Goldman, 1970, p. 10), we may ask, is the consumer performing one action here (e.g., "the consumption of air conditioning filters") or up to five actions? Our answer to this question will do much to explain what we mean by consumer action, how we go about explaining and interpreting consumer action, and what role consumer behavior as defined above plays in this regard.

Many complex philosophical issues are involved in conceiving of consumer action in the example above as either a single action described in five different ways or as a collection of so-called act-tokens consisting of separate, specific actions related among themselves in some way. It is beyond the scope of this chapter to resolve the issues here, but it seems helpful to use a statement that Aristotle made long ago to highlight the components of consumer action and its relationship to consumer behavior and goals. Aristotle said, "The first principle of action—its moving cause, not its goal—is rational choice, and that of rational choice is desire, and goal-directed reason" (Aristotle, 2000, p. 104)[2].

Unpacking Aristotle's seemingly simple description of action, and at the risk of oversimplification, we might say that action is what one does as an agent either as an end in and of itself or as a means to achieving a goal. Moreover, this action is determined proximally by choice (roughly comprised of such volitional processes as decision making and intention formation), whereas choice is determined by desire, and desire by goal-directed reasoning, where the latter encompasses in part cognitive processes and more broadly what might be termed *reasons for acting*.[3] Schematically, we might summarize intentional or purposive action in this regard as follows: reasons for action → desire to act → decision making/choice/intention to act → action (as an end or means to an end) → achievement of an end → collateral outcomes.[4]

With this sketch of the meaning of action, we can return to the consumption example posed above, where I claim that there is neither one overall action nor solely a series of interconnected actions. Rather, we have a description of three "shopping" *actions* in sequence, followed by "use" of the products purchased, then "achievement" of the objective for which the shopping and use were intended, and finally "production" of a post-goal outcome. That is, shopping here consists of (1) walking down the aisle and searching for the filters, (2) reaching for and placing the filters in the cart, and (3) paying for the filters at the check-out. The filters are next installed, which constitutes an act of *usage,* or at least the first step in this regard. The actions of shopping and installation then are means to the *goal* of improved air quality. Disposing of the old filters is a secondary action with its own objectives (e.g., keeping the home from being cluttered, fulfilling preplanned recycling goals), whereas adding to rubbage in the environment is an *outcome* of goal attainment. Notice that distinctions exist among shopping and usage, which are two types of consumer action, and goals and outcomes. Researchers have frequently confused goals and outcomes with actions, and they have sometimes claimed that such mental events as decisions, choice, intentions, and planning are actions. This has led to misleading claims and certain confounds between action proper and its antecedents and consequences over the years. Neglected, too, has been study of the role of cognitive processes throughout the multiple stages of consumer action.

More formally, we might say that action is "what an agent does, as opposed to what happens to an agent (or what happens inside an agent's head)" (Blackburn, 1994, p. 5). Three closely related aspects of this definition deserve emphasis. The first is the concept of an agent and the notion of *agency,* which can be described as follows: An agent is "one who acts. The central problem of agency is to understand the difference between events happening in me or to me, and my taking control of events, or doing things" (Blackburn, 1994, p. 9). Second, action deals with what a person does in a self-regulative or willful way. Third, to the preceding definitions, we should include consideration of what actions lead to and why actions are undertaken, which are discussed below under the sections that follow Automaticity in Action. In other words, action is typically goal directed, though it can be totally expressive on occasion as well (Bagozzi, 2000a; Bagozzi and Dholakia, 1999). But it is important to recognize that the reasons why actions are performed and what actions lead to are distinct from the actions themselves.

Consumer action, then, is something a person does in the acquisition, use, or disposal of a product or service. The "doing" needs further specification, but it is important to stress that doings go on at multiple stages of consumer action: before acquisition, during acquisition, and after acquisition, of a product or service. Moreover, in some sense the doer or agent actively and intimately engages in the doings. More than bodily movements and subsequent outcomes are involved; action involves agency. Before we elaborate on important aspects of doings and consider the deliberative path to consumer action, it is helpful to consider the automatic path because it also initiates action seemingly directly, yet interacts with deliberative processes in certain instances as well.

## Automaticity in Action

### *The Impulsive System*

At first glance, it may seem incongruous to characterize action in the same breath as automaticity. But unconscious processes have been shown to play a role in at least some actions.

One way this occurs is in the acquisition of skills or well-learned action routines and their execution. The daily trips to the university coffee machine appear to be a case in point. The first few times I went to the machine to buy a cup of coffee, I executed a series of perceptual, cognitive, and motor skills that required a lot of conscious attention, given how complex the operation of the new machine was with all its choices: "regular," "50–50," or "decaf"; "French roast," "café mocha," "hot chocolate," or "hot water"; "mild," "medium," or "strong"; "1/2 cup," "regular cup," "tall cup"; "carafe"; "start." But the more frequently and consistently I made my choices, over time, the less conscious attention I had to allocate. With experience, my purchase of coffee now occurs with little conscious attention at all and is, in effect, automatic.

Or is it? It is clear that my decision to move to the vending machine area to get a cup of coffee is deliberate. It springs from an internal physiological urge or external cues around me, such as the sight of a person drinking coffee or its aroma, and is expressed in an intention to go to the coffee machine for the purpose of acquiring "my regular cup of coffee." But once I get to the machine, the actions of selecting buttons and pushing them in the order I typically do are activated and in a sense controlled by the now familiar environmental cues on the machine. The instrumental acts are automatic or habitual. In sum, once I decided to get the coffee, the actions subsequently taken to do so were largely unconscious and automatic. This is an example of the deliberative system initiating action steps and their control via the automatic system. Here reflective processes activate impulsive (or compulsive) actions. Vera and Simon (1993) discuss some of the elements of this sense of the activation of unconscious actions by conscious intentions.

But can action be initiated automatically without a conscious decision to do so? Bargh (1990) describes just such an automatic process in his "auto-motive" model. That is, a person's chronic goals or motivations can be triggered directly by environmental stimuli, in certain instances, and then guide cognitive and motor processes in goal pursuit. Goals become associated with mental representations of environmental cues through frequent and consistent co-activations. Bargh and Barndollar (1996, p. 464) summarize automaticity as follows: "if an individual frequently and consistently chooses the same goal within a given situation, that goal eventually will come to be activated by the features of that situation and will serve to guide behavior, without the individual's consciously intending, choosing, or even being aware of the operation of that goal within the situation." In other words, perception leads to purposive action through unconscious processes in this case.

In addition to goal activation, Bargh (1997) claims that any skill—cognitive, motor, or perceptual—can become automaticized. This has also been observed for the unconscious imitation of social behavior (Bargh and Ferguson, 2000; Dijksterhuis, Bargh, and Miedema, 2000).

Automatic processes in the sense described above are formed in one of two ways. First, associations structured by similarity and contiguity are formed through repeated experiences and occur preconsciously (Smith and DeCoster, 2000, p. 111). Second, conscious representations in the deliberative system, which entail propositional knowledge (discussed later in the chapter), activate corresponding content in "a simple associative network" in memory (Strack and Deutsch, 2004, p. 223).

Strack and Deutsch (2004) call the functioning of associative links an "impulsive system," which corresponds to our "automatic processes" in Figure 1.1. Connections in the impulsive system are made through a mechanism of spreading activation whereby a perception of a stimulus or imagination of a concept leads to greater accessibility of associated contents in memory. For example, the smell of fresh brewed coffee might activate such interconnected concepts as "delicious," "thirst quenching," "Starbucks," "comforting," "satisfying." These concepts or the aroma itself might directly energize a behavioral schema like the one alluded to above, "get coffee!"

The nature of associations among concepts in the impulsive system is believed to be one of mutual activation and does not contain semantic meaning by itself. In addition, the organization of associations and concepts is hierarchical by level of abstractness. Although the content of the impulsive system is conceptual or categorical, a person typically is only aware experientially of its phenomenal quality, unlike the experience of deliberative processes where one is aware of reasoning, making inferences, drawing conclusions, and so on. For instance, the pleasantness of the aroma of coffee occurs in the impulsive system as a pleasant feeling, not knowledge of the concept of pleasantness.

We have already mentioned how a deliberative decision or intention might activate automatic processes in the impulsive system. But the direction of influence can go in the other direction, from the impulsive system to the deliberative system. Association links in the impulsive system might bias perceptions or judgments, for example, or a syllogistic proposition used in the deliberative system can be based on retrieval of its well-learned content from the impulsive system.

### *Automatic Approaches to Attitudinal Processes*

The automatic, effortless, and implicit aspects of human information processing are currently at the center of attention in attitude research. Several recent studies have shown that implicit attitudes can be activated automatically and guide behavior directly (e.g., Bargh, Chen, and Burrow, 1996; Chen and Bargh, 1999; Dovidio, Kawakami, Johnson, Johnson, and Howard, 1997; Fazio and Dunton, 1997). Other studies have found that attitude accessibility moderates the link between attitudes and behavior (e.g., Fazio, Sanbonmatsu, Powell, and Kardes, 1986; Fazio and Williams, 1986; Posavac, Sanbonmatsu, and Fazio, 1997). Fazio's MODE model encapsulates this empirical evidence by proposing that attitudes that are automatically accessed, via strength of the object-evaluation association, bias perceptions of the object and lead directly to behavior without any conscious reasoning processes occurring (Fazio, 1990). Still other studies have emphasized implicit attitudes that are thought to direct people's reactions to attitude objects outside of conscious awareness (Greenwald and Banaji, 1995). The Implicit Association Test (IAT) (Greenwald, McGhee, and Schwartz, 1998) has been specifically developed to measure implicit attitudes and has been used in several studies (e.g., Cunningham, Preacher, and Banaji, 2001; Dasgupta, McGhee, Greenwald, and Banaji, 2000; Greenwald and Farnham, 2000; Forehand and Perkins, 2004; Greenwald, Banaji, Rudman, Farnham, Nosek, and Mellott, 2002). Altogether, there is growing and convincing evidence that automatic processes play an important role in human cognition and that they can direct behavior even when it is complex (e.g., Bargh, Gollwitzer, Lee-Chai, Barndollar, and Trötschel, 2001).

To date, however, we do not have a good sense of the magnitude of the effects of automatic processes on action and the relative importance of deliberative versus unconscious processes in this regard. Perugini and Bagozzi (2004a) used a procedure suggested by Rosenthal and Rubin (1982) to calculate the variance explained in behavior as a result of automatic processes for 18 dependent variables across 10 experiments reported by Bargh et al. (1996), Chartrand and Bargh (1999), and Dijksterhuis and Van Knippenberg (1998). The amount of variance explained in behavior due to the automaticity manipulations ranged from 0.01 to 0.37 with a mean of 0.13. Thus, automaticity explained only 13% of the variance in behavior on average.

As points of comparison with respect to deliberative models of attitude processes and their effects, it can be noted that Godin and Kok (1996) found that on average 34% of the variance in behavior was explained in 76 applications they examined of the theory of planned behavior (TPB); Armitage and Conner (2001) found that on average 27% of the variance in behavior was explained in 185 empirical applications they investigated of the TPB; and Sheeran (2002) found in his meta-analysis (sample $N = 82{,}107$) that 28% of the variance in behavior was explained by the TPB and related models. In sum, considerably more variance has been explained in behavior by studies using deliberative models in comparison to studies using automatic process models.

When studying deliberative processes, psychologists and consumer researchers have on occasion used habit or past behavior as methodological controls or even as proxies for automatic decision making and heuristic processing (Bagozzi, 1981; Bagozzi and Warshaw, 1990; Ouellette and Wood, 1998; Verplanken and Aarts, 1999). Ouellette and Wood (1998) proposed two processes through which frequency of past behavior guides future behavior. When a behavior is well learned and practiced in a nonchanging environment, frequency of past behavior reflects habit strengths and therefore has a direct effect on future behavior. When a behavior is novel or is performed in nonstable contexts, frequency of past behavior influences decision making or intentions on the supposition that people like to do things that they have done in the past. Bagozzi and Warshaw (1990) examined both frequency and recency of past behavior and their effects. Recency effects in particular were suggested to reflect availability and anchoring/adjustment biases and influenced subsequent behavior, whereas frequency effects occurred on intentions.

Aarts and Dijksterhuis (2000) define habit as a form of goal-directed automatic behavior, which is activated automatically by the presence of relevant environmental cues, provided that the relevant goal is activated. Ajzen (2002b) puts forth a different view on habit and maintains that no theoretical support exists for the manner by which habit is said to function. Instead, such things as the instability of intentions or the presence of unrealistic optimism and inadequate planning provide more grounded accounts for behavior than habit.

The study of automaticity is difficult to carry out in field studies and survey research. Until the technology of studying automaticity and impulsive action advances, some gain may accrue by including the frequency and recency of past behavior as measures in our studies.

I do not wish to claim that deliberative and unconscious processing are mutually exclusive explanations of action. Sometimes action will be a function of deliberative processes, sometimes automatic processes, sometimes both deliberative and automatic processes. The determination of action is very much under dual control by automatic and deliberative processes, and it is important in the future to study in depth how and under what conditions one or the other or both function. We turn now to an emerging framework for looking at deliberative processes, which has occupied much of my efforts over the years.

## Intentional Consumer Action

Goldman (1970, p. 76) defines intentional action as action that "the agent does *for a reason.*" This definition captures the starting and end points of intentional action well, but says nothing about how, or by what processes, reasons lead to actions. What a person does in a deliberative, reflective sense starts off with his or her reasons for acting, but the nature of these reasons and how they function need specification and elaboration. Furthermore, there is more to the initiation of action than reasons for acting. In this section of the chapter, I consider the two most proximal determinants of action: attempts to act and intentions to act. Then in subsequent sections, I turn to a discussion of the key reasons for action, the role of desires as essential motivational processes transforming reasons into decisions and plans, and finally to the self-regulation of action, which is where agency comes to the fore.

### *Trying to Consume*

Acts of consumption are engaged in as either ends in and of themselves (e.g., dancing simply for its aesthetic and kinesthetic pleasures) or means to other ends (e.g., exercising and dieting for the purpose of losing weight). In either case, consumers initiate acts by attempting or trying to act.

What exactly is trying to act? Answering this seemingly simple question might be best approached by starting with a philosophical query. Wittgenstein (1997, p. 161e) once posed the following puzzle: "When I raise my arm, my arm goes up. And the problem arises: what is left over if I subtract the fact that my arm goes up from the fact that I raise my arm?" Bagozzi and Warshaw (1990) answered this question by stating that "trying to act" is the residual (but see Ryle, 1949). The idea is that consumers often realize that performance of an intended act is problematic in their own minds because they recognize either that they have personal shortcomings (e.g., limited resources, weakness of will) or that situational conditions might thwart action (e.g., bad weather or a traffic jam might arise en route to a planned shopping spree). To perform an end-state consumption act or fulfill one's consumption goals, then, a consumer must see his or her own action as a purposive endeavor where foresight and effort are needed to execute an experiential act of consumption or achieve a consumption goal or outcome. Rather than being under total control, consumer action is thought to be under partial control, and a consumer decision maker focuses on activities believed to be required for experiencing consumption or by shopping for, buying, using, or disposing of a product or service.

Bagozzi and Warshaw (1990) conceived of trying as a singular subjective state summarizing the extent to which a person believes that he or she has tried or will try to act, including the effort put forth in this regard. Trying was presumed to mediate the influence of intentions to act on actual actions.

Without denying that consumers sometimes form subjective senses of past, current, or anticipated tryings, Bagozzi (1992) deepened and broadened the concept of trying to embrace a set of psychological and physical processes engaged in after forming an intention to act in order to implement the intention. It should be mentioned that some controversy exists in the philosophy literature regarding where to draw the line between inner events and bodily movements, with some equating particular instances of the former and others the latter to types of tryings (e.g., Pietroski, 2000). Bagozzi (1992) proposed that, following a decision to act, some subset of the following might constitute trying: planning, monitoring of progress toward a goal, self-guidance and self-control activities, commitment to a goal or intention or action, and effort put forth. Note that the realization of trying often occurs as a process or series of mental and physical coordinated instrumental strivings, where some of the above events are repeated but in unique ways.

Bagozzi and Edwards (1998) tested a portion of the above-mentioned trying processes in a study of body weight loss/maintenance. Here the authors operationalized trying as separate mental events and physical activities used to initiate and regulate instrumental actions (i.e., exercising and dieting) to achieve one's weight loss/maintenance goals (see also Bagozzi, Baumgartner, and Pieters, 1998; Bagozzi, Baumgartner, and Yi, 1992). Trying included maintaining willpower and self-discipline, devoting time for planning with respect to instrumental acts, and expending physical energy in goal pursuit. Taylor, Bagozzi, and Gaither (2001) developed measures of trying further in their study of the self-regulation of hypertension by focusing on four aspects of trying to act in order to reduce/maintain blood pressure: (1) devoting time to planning, (2) expending mental/physical energy, (3) maintaining willpower, and (4) sustaining self-discipline. Finally, still other facets of trying were investigated by Bagozzi and Edwards (2000), who found that appraisals of the means for acting (in the forms of self-efficacy, outcome expectancies, and affect toward the means) interact with the strength of impediments to goal achievement to regulate goal-directed behaviors in the pursuit of weight loss/maintenance goals.

Further thought is needed on how to conceive of trying. Is it only a subjective overall sense of trying? Or is it constituted by multiple mental states or events and physical effort applied at different points in time between making a decision to act and actual acting? Some philosophers seem to take an even broader view of trying to include intentions, volitions, and certain "actions" that precede bodily movements (e.g., Hornsby, 1980; Pietroski, 2000). The line, then, between trying and intentions, volition, and goal-directed behavior may be difficult to draw, and an argument could be made that *trying* is an omnibus term implicating all the events and processes alluded to previously that intervene between intention formation and planning, on the one hand, and action initiation, on the other hand. Nevertheless, even if trying is construed as merely a label for many things, this does not diminish the likely reality that one or more of the mental and physical events and processes discussed as aspects of trying are essential in the explanation of consumer action. Sometimes merely one aspect, at other times many aspects, of trying might be important in accounting for and predicting consumer action.

In whatever sense trying is construed, it is important to think of goal striving, particularly in the latter stages, as a process, as alluded to above. Monitoring one's progress in goal pursuit is an important activity with self-regulatory implications. Carver and Scheier (1998) propose that two feedback systems function to guide action in such contexts: approach and avoidance processes. These are affective responses that occur in reaction to appraisals of one's progress toward a goal such that, when the rate of progress is below a reference value, negative affect occurs, and when the rate of progress is at or above the reference value, positive affect results. Furthermore, one bipolar affect system (elation–sadness) manages the approach of incentives, whereas another bipolar affect system (relief–anxiety) manages the avoidance of threat, where both occur in response to doing well or doing poorly with respect to incentives or threats to goal progress, respectively. I suggest that this affective feedback system *moderates* the ultimate effect of trying on goal success or goal failure. When progress is made in pursuit of either a sought-for incentive or avoidance of a threat, one feels elated or relieved, respectively, and the action implication is to stay the course. When progress wanes in pursuit of an incentive or avoidance of a threat, one feels sad or anxious, respectively, and the implication is to try harder to achieve the goal. Of course, when consumers try to achieve a consumption goal, they sometimes alter the target goal or their definition of success or failure; indeed, they even might abandon goal striving. The bottom right of Figure 1.2 captures the above discussion, where we see that affect from appraisals of the rate of progress in goal pursuit moderates the effect of trying on goal attainment/failure. Instead of the two bipolar affective systems suggested by Carver and Scheier (1998), there may in fact be four separate unipolar systems corresponding to elation, sadness, relief, and anxiety, respectively (Bagozzi, Wong, and Yi, 1999).

A somewhat different approach to the management of goal striving and the role of emotions has been proposed by Oatley and Johnson-Laird (1987, 1996) in their communicative theory of emotions. Emotions are seen as interrupt mechanisms that alert a single decision maker or multiple decision makers working together that progress in goal pursuit deserves attention. Emotions occur “at a significant juncture of a plan . . . when the evaluation . . . of the likely success of a plan changes” (Oatley and Johnson-Laird, 1987, p. 35). For example, when a subgoal is achieved, happiness occurs; when a plan fails, sadness happens; when a plan is frustrated, anger results; and when a goal related to one’s physical well-being or when social well-being is threatened, anxiety arises. These emotions can refer to a sought-for goal object or can arise as a consequence of unplanned happenings. Oatley and Johnson-Laird (1996) also considered emotions that apply only to a personally held goal: attachment, disgust, love, rejection, and sexual attraction. The experience of each emotion is tied to specific action consequences. For example, when we are happy as progress in goal pursuit occurs, we persevere in fulfilling our plans; when our progress fails at particular junctures, we become dejected, and depending on other individual difference or situational support, we give up, search for an alternative plan, or work harder on the original plan; likewise with anger in relation to frustration of an ongoing plan, we often try harder. The function of emotion at this stage of goal striving is to prepare the decision maker for acting adaptively and efficiently without the need for complex and potentially time-consuming reasoning processes. A similar point of view on the role of emotions in goal striving can be found in Stein, Trabasso, and Liwag (2000).

### *Intentions*

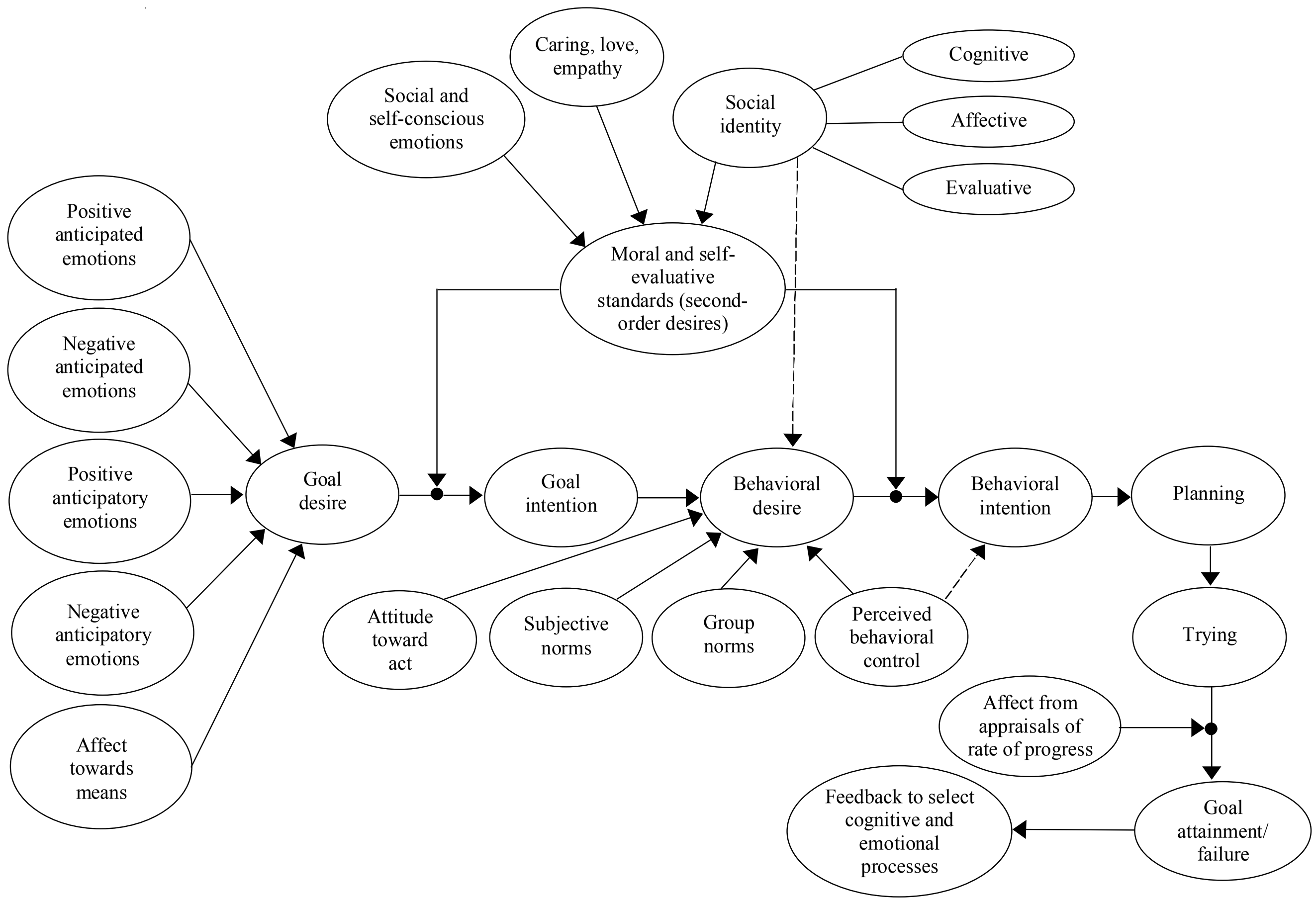
Trying and the action it results in are products of volition. Lewin summarizes nicely the role of volition in action:

> [A] complete intentional action is conceived of as follows: Its first phase is a motivational process, either a brief or a protracted vigorous struggle of motives; the second phase is an act of choice, decision, or intention, terminating this struggle; the third phase is the consummatory intentional action itself. (Lewin, 1951, pp. 95–96)

The first phase will be discussed later in this chapter under Desires to Act. Desires actually can be shown to be functions of reasons for acting, which is the subject in the next major section of the chapter. It is in the second phase that volition occurs, which is the topic in this section. As intimated above, the line between volition and trying, like that between trying and action, can become blurred, and especially becomes difficult to draw when volition and trying occur complexly in multiple stages.

What exactly is volition? As a working definition, we prefer to conceive of volition as the decisions, choices, intentions, and plans one makes to achieve an object of desire or to perform desired acts. Again the acts can be ends or means to ends. In this sense, we limit volition to

Figure 1.2 **Summary of Key Variables and Processes in Consumer Action as a Deliberative and Reflective Endeavor**




*Note:* The effects of habit, past behavior, and automatic processes are omitted for simplicity.

mental events, and we reserve the term *trying* for both mental and physical effort expended in goal pursuit or end-state behavioral activity. Notice, however, that when sequences of decisions and instrumental acts are performed, volition often occurs throughout the process, and we can appreciate how volition and trying often alternate repeatedly when one strives for a goal or engages experientially in an activity for its own sake. A case in point happens when a person monitors progress in goal pursuit and applies guidance and control responses to regulate the likelihood of goal achievement. It should be mentioned, too, that volition often functions along with complex self-regulative or willful processes, which we consider near the end of the chapter.

For a long time, the concept, intention, has been regarded as “the immediate determinant of behavior” (Ajzen and Fishbein, 1980, p. 41). This might be true in some cases in which one acts straightaway after making a decision to act (e.g., selecting a particular brand of soft drink from a machine after approaching it with no particular brand in mind simply to enact one’s intention to quench a thirst). But as discussed previously, many mental events and physical actions frequently mediate or moderate the effects of intentions on a final act and likely do so in mundane, as well as complex, situations.

Notwithstanding the direct or indirect role of intentions in consumer action, it should be acknowledged that intentions occupy a unique place in consumer action because intentions, on the one hand, transform reasons to act (the most studied phenomena in the field to date) and motivations to act into attempts to act, actual action, and ultimately goal attainment, on the other hand. But surprisingly, a rather simple and naïve conception of intention seems to characterize its use in consumer research.

So what exactly is an intention? At the outset, we might point out that consumer researchers have used three terms more or less interchangeably to capture the meaning of this frequently used idea: intention, decision, and plan. Choices often fall under the category of intentions as well because they are framed most frequently as hypothetical mental commitments and they are typically framed without the occurrence of costs or action requisites and consequences taken into account in their regard. It is not difficult as well to identify confusion and inconsistency in use of the term *intention* in the basic discipline from which the concept has been borrowed. On the one hand, perhaps the narrowest definition can be attributed to Allport (1947, p. 186): “Let us define intention simply as *what* the individual is trying to do.” Heider (1958, pp. 83, 108) also largely adopted this point of view. One might argue that this outlook potentially begs the question of what it is to act intentionally because it focuses too closely and nearly exclusively on the referent of intentionality. I say “potentially” here, because this definition is especially a problem in the theory of reasoned action (TRA) and the TPB, which do not consider desires or trying, but, where the concept of intention is asked to do too much and is measured in a rather restricted and inconsistent way, yet might not be a problem in expanded frameworks in which trying and desires to act are included as well, along with intentions. I discuss this matter in greater detail in the following sections.

Ajzen (1991, p. 181) gave perhaps the broadest interpretation of what an intention is when he proposed that intentions “are indicators of how hard people are willing to try, of how much of an effort they are planning to exert.” This definition includes trying, effort, and planning, but Ajzen (1991) never developed these separate concepts, and it is unclear whether he meant them to be part of or constitutive of intentions, or correlates or merely suggestive of intentions (“indicators”). The evidence seems to favor the latter interpretation, for neither in his previous work (e.g., Ajzen and Fishbein, 1980; Fishbein and Ajzen, 1975) nor his subsequent research (e.g., Ajzen, 2001, 2002a; Ajzen and Fishbein, 2004) have these aspects of volition or trying been incorporated formally into his concept of intentions. In other words, the concept of intentions remains vague and undeveloped in the TRA and the TPB.

To gain a sense of what Ajzen means by *intentions,* we must rely on how he operationalized it in his empirical studies. Here intention is measured as the likelihood ("very unlikely" to "very likely") that one intends to do something (e.g., Ajzen and Fishbein, 1980, ch. 4). In essence, Ajzen and Fishbein regard intentions as self-predictions or expectations that one will act (cf. Bagozzi, Baumgartner, and Yi, 1989).[5]

I believe that this treatment of intention is too narrow and too empirically construed. Intentions, as distinct from trying and from the motivations to act considered subsequently in this chapter, are multifaceted concepts that play important roles in directing one's motivation to act toward appropriate actions and toward the initiation of planning and related mental and physical activities needed to implement goal-directed behaviors. We turn now to the various kinds of intentions.

### *Personal Intentions (I-intentions)*

The common-sense notion of intentions, and the one most frequently studied in research, is the person's commitment, plan, or decision to carry out an action or achieve a goal by himself or herself alone (Eagly and Chaiken, 1993). For example, "I intend to begin reading bestselling novel X this evening" or "I intend to lose weight." The referent of an I-intention is a personal act or goal, and it both predicts the personal act or goal in question and is explained by reasons for acting or wanting to achieve the goal that the person holds.

### *Goal Versus Implementation Intentions*

One can see two other kinds of intentions in the distinction between goal and implementation intentions. A *goal intention* is a self-commitment to realize a desired end state and might be expressed linguistically in the form "I intend to pursue X" (Gollwitzer, 1993, p. 150). It typically occurs early in decision-making processes and precedes consideration of how to pursue a goal. An *implementation intention* is a self-commitment to perform a particular action and might be expressed linguistically as "I intend to initiate behavior X whenever the situational conditions Y are met" (Gollwitzer, 1993, p. 152). Notice that the implementation intention here is stated contingently. Actually, both goal and implementation intentions can be affirmed noncontingently or contingently. Thus, for instance, a goal intention to purchase a high-definition television (HDTV) might be phrased, "I intend to acquire an HDTV" or "I intend to acquire an HDTV only when the price drops below $2000." Similarly, examples of implementation intentions are, "I intend to exercise tomorrow afternoon" and "I intend to exercise tomorrow afternoon if my sore calf muscle has healed sufficiently." Bagozzi, Dholakia, and Basuroy (2003) and Dholakia and Bagozzi (2003) investigated different functioning of goal and implementation intentions. Notice where goal intentions and implementation intentions (labeled, behavioral intentions) occur in the framework presented in Figure 1.2.

Implementation intentions mediate the effects of goal intentions on action (but often along with other variables described here subsequently). In this regard, Gollwitzer and Brandstätter (1997) propose that implementation intentions serve two functions. Cognitively, implementation intentions provide mental representations of the opportunities implied by the intentions. It is believed that these would "attract attention, be easily remembered, and be effectively recognized" in a relevant situation occurring at a future point in time when the intention is to be fulfilled (Gollwitzer and Brandstätter, 1997, p. 196). Volitionally, implementation intentions "create strong mental links between intended situations and behaviors" and "in the presence of the critical situation, the intended behavior will be elicited automatically" (Gollwitzer and Brandstätter, 1997, p. 196).

Gollwitzer (1996) has conceived of implementation intentions as a cluster of decisions concerning when, where, how, and how long to act. I would prefer to reserve the when, where, how, and how long to constitute aspects of planning, which occurs most frequently after formation of an intention to act, and in any case is distinct from that intention itself. Thus, I would prefer to think of an implementation intention as the decision to perform a behavior in the service of goal attainment (hence termed, behavioral intention in Figure 1.2). The measurement of this specific goal implementation intention might be done with the likelihood items proposed by Ajzen and Fishbein (1980), but a more direct measure would be to ask respondents to indicate how strong their intention is to act in a particular way (e.g., "not at all," "very weak," "weak," "moderate," "strong," "very strong") or how committed they are to act so as to achieve their goals.

### *Collective Intentions*

Drawing on the works of contemporary philosophers, I proposed that intentions can be social in some sense, to contrast with the more common conceptualization of I-intentions (Bagozzi, 2000b; Bagozzi and Christian, 2005; Bagozzi and Lee, 2002). For example, a person in an intimate relationship might speak of "*our* intention to see Tchaikovsky's *Swan Lake*"; a football player might mention "the *team's* plan to implement a new defensive scheme"; a corporate executive might announce "the *firm's* hostile intention to take over another firm"; and the president of the United States might remark that "the *American people* intend to win the war over terrorism." These examples—referring, respectively, to a two-person dyad, a small group, an organization, and a collectivity—illustrate that people often use social notions of intentions in ordinary speech, whether referring to informal or formal groups. The conceptualization, measurement, and functioning of collective intentions differ fundamentally from classic conceptions of intentions.

I suggest that there are two classes of collective intentions. One is a personal intention to do something with a group of people or to contribute to, or do one's part of, a group activity (e.g., "I intend to practice with my jazz ensemble this Saturday afternoon," "I intend to help collect signatures for referendum X with my compatriots in the local chapter of political party Y"). Notice that a person can have an intention to act as an actor, yet the action can be self-construed as an individual act performed alone (an I-intention to do an individual act) or as a member of a group (an I-intention to do one's part of a group act). Either way, the intention is still an I-intention because the person sees himself or herself autonomously performing an action. An I-intention is an individual intention when one intends to act alone in a personal activity; it is a collective intention (i.e., an I-intention to participate as a member of a group) when one intends to act as part of a group activity (e.g., an intention to do one's part of a group project).

A qualitatively different form of a collective intention is what we might call a "we-intention." A we-intention is a collective intention rooted in a person's self-conception as a member of a particular group (e.g., an organization) or social category (e.g., one's gender, one's ethnicity), and action is conceived as either the group acting or the person acting as an agent of, or with, the group. I propose further that we-intentions exist in two closely related versions. The first is the shared we-intention and is expressed in the form "I intend that our group/we act" (e.g., "I intend that our family visit Sea World, San Diego, next vacation"). The second version of the we-intention is communal and framed in the form "We (i.e., I and the group to which I belong) intend to act" (e.g., "We intend to sponsor an exchange student next year").

A number of studies have examined group-oriented I-intentions and we-intentions in recent years. Bagozzi and Lee (2002) studied small face-to-face friendship groups; Bagozzi and Dholakia

(2002), Bagozzi, Dholakia, and Klein Pearo (2005), Dholakia, Bagozzi, and Klein Pearo (2004), and Bagozzi, Dholakia, and Mookerjee (2005) investigated virtual communities; Bagozzi, Dholakia, and Mookerjee (2005) examined face-to-face collaborative browsing groups; Bagozzi and Christian (2005) scrutinized small face-to-face tutorial groups; and Bagozzi and Dholakia (2005a, b) studied brand communities.

*The Functioning of Intentions*

Most commonly, intentions have been construed as instigators of action that mediate the effects of cognitive responses and motivation to act on action. Nevertheless, some evidence exists that certain processes moderate the effects of intentions on action as well. Bagozzi and Yi (1989) found that the degree of well-formedness of intentions is an important factor in their operation. When intentions are well formed, they completely mediate the effects of reasons for acting. When intentions are poorly formed, they only partially mediate the effects of reasons for acting, which also have direct effects on action as well. Bagozzi, Yi, and Baumgartner (1990) found that the level of effort required to perform an action also moderates the effect of intentions on action. When the enactment of an action requires substantial effort, intentions fully mediate the effects of reasons for acting; when enactment requires little effort, reasons for acting, particularly attitudes, have direct effects as well as indirect effects through intentions.

Dholakia and Bagozzi (2003) showed that goal and implementation intentions not only work through different psychological mechanisms but also interact to influence action. Two situations they studied were how goal-commitment-driven intentions (where a person has a well-formed goal intention but a poorly formed implementation intention) and plan-driven intentions (where a person has a well-formed implementation intention but a poorly formed goal intention) operate. The former is consistent with the normal or common sequence of the effects of intentions, where in this case, however, commitment to a goal, for whatever reasons, does not lead to a strong implementation intention that is bolstered by planning. The latter occurs, for example, when an intention is externally imposed through instructions, orders, or inducements. (Kvavilashvili and Ellis, 1996, term this type of intention *other-generated intentions*). Dholakia and Bagozzi (2003) found that goal-commitment-driven intentions were more effective than plan-driven intentions when the action task was difficult, whereas the opposite occurred for low task-difficulty situations. In other words, the goal-driven intentions proved to be more motivating in a largely deliberative context, whereas the plan-driven was more functional in an automated-like context where transference of control was done from deliberative, ongoing processing to situational cues identified in the planning process. In another experiment, Dholakia and Bagozzi (2003) showed that the greatest success in acting as planned occurred when both goal and implementation intentions were well formed, as opposed to both ill-formed or one or the other ill- or well- formed. Their research was conducted in the context of "short-fuse behaviors," which are actions that must be performed within a limited window of opportunity for success (e.g., catching a train on-time, returning rented movies before incurring a fine, or purchasing a ticket for an anticipated high-demand concert).

## Reasons for an Action

A number of bases for acting enter decision-making processes en route to the formation of an intention to act. We can define *reasons for action* as "considerations that call for or justify action" (Audi, 1995, p. 677). The reason(s) that account for or actually cause an action typically do so indirectly through intentions and might be termed *explaining reasons*. Davidson (1963) gave a classic argument for explanatory or causal reasons in this sense. I develop how explanatory reasons determine action subsequently in this and the following sections. *Practical reasoning* can be defined as "the inferential process by which considerations for or against envisioned courses of action are brought to bear on the formation and execution of intention" (Audi, 1995, p. 636). Philosophers use the term *inferential process* to refer to formal thinking processes in which conclusions are drawn from premises, as well as processes involving argument, intelligence, and insight. The *Concise Routledge Encyclopedia of Philosophy* (2000) points out that there are two kinds of practical reasoning: instrumental, which "identifies ways of reaching certain results or ends," and ethical, which identifies "important ends." Important ends are not evaluated only by moral criteria in everyday decision making but by one's values more generally. Reasons for an action are taken in this chapter as content used in deliberative thinking processes to reach decisions. They constitute such concepts as attitudes, beliefs, values, normative beliefs, moral beliefs, and perceived behavioral control. Many researchers use these concepts in a different and more restricted sense in that the concepts are presumed to function causally in a deterministic way, yet do not enter reflectively in a person's deliberations.

A distinction can be made between reasons and motives. Reasons are considerations that might enter decision making and concern things that we can come to see either as rewarding, pleasurable, or good or as punishing, displeasurable, or bad. But a decision maker need not accept reasons for action as such as a personal motive to act, and therefore these reasons need not explain an action taken by the decision maker. I may recognize, for instance, that a sports car is attractively styled, superb in handling, and affordably priced, yet not be motivated to buy it or not even be motivated by these attributes. Indeed, I may be motivated not to buy sports cars because of a commitment to a frugal life-style, promotion of ecology, or some other requisite, despite acknowledging the aforementioned positive attributes. A reason for an action can become a motive to act but must go through further reasoning and decision processes (or else become functional in the impulsive system through acquisition of action-initiating forces resulting from such prior processes as operant conditioning, automatic emotional responses that have been hard-wired through our biological evolution, or the activation of behavioral routines via unconscious processes or implicit attitude processes similar to those described above).

Notice that many things that I claim are reasons for acting (e.g., attitudes, subjective norms) are implicitly assumed to be motives for acting by many consumer researchers. But I would argue that even demonstrating an empirical association between attitude and action, or even between attitude and intention to act, does not necessarily show that attitude has emotive power to bring about action or the decision to act, respectively. Before a reason for action can causally determine a decision or lead to intention formation in the reflective, deliberative system of information processing, it must be accepted as such by the decision maker. Even then, the self-acknowledged personal reason for acting may not result in a decision to act or formation of an intention to act. After all, we often have many reasons for acting or not acting, and these reasons frequently conflict. Before a decision is made or an intention is formed, the multiple self-accepted reasons for acting must become reconciled and transformed. This is done primarily through the functioning of our desires, which serve as a summary motive for wanting each goal we might have (a goal desire) and for doing each action conducive to achievement of each goal that we might consider (a behavioral desire)—hence the labels "goal desires" and "behavioral desire" in Figure 1.2. The role of desires will be discussed more fully in the next major section of the chapter.

Reasons for acting are in a sense actively processed and interpreted by a decision maker. My colleagues and I have characterized the process as a fourfold application of the following procedures: consider–imagine–appraise–decide (e.g., Bagozzi, Moore, and Leone, 2004, pp. 201–

202). I will elaborate on these processes in a moment, after I provide some more background.

The reflective, deliberative system generates and processes knowledge that is based on internal and external information. This occurs in the forms of rule-based processing, propositional categorizations, and syllogistic inferences (e.g., Smith and DeCoster, 2000; Strack and Deutsch, 2004). Rule-based processing "draws on symbolically represented rules that are structured by language and logic and can be learned in just one or a few experiences" (Smith and DeCoster, 2000, p. 111). Declarative knowledge in the reflective, deliberative system results when perceptual input is assigned to a semantic category. Specifically, "knowledge . . . consists of one or more elements to which a relational schema is applied . . . [and] a truth value is assigned to that relation" to generate semantic and episodic knowledge (Strack and Deutsch, 2004, p. 224). The outcomes are representations of states of the world expressed in propositional formats. Strack and Deutsch (2004) claim that the elements of propositions are retrieved from the impulsive system. The operations of inference making and generalization underlying this process are described by Hummel and Holyoak (2003). In addition to logical relations (e.g., "is a," "is not," "implies"), causal and social relations are represented in propositions.

Strack and Deutsch (2004) describe how syllogistic rules are applied to information in the reflective, deliberative system for the purpose of drawing inferences going beyond the information represented therein. This process is different from the generation and access of associations in the impulsive system, which is based on spreading activation mechanisms. Rather, under syllogistic and other rules and relations found in the reflective, deliberative system, reasoning drives the process, and decisions determine goal setting and goal striving. Finally, unlike the experiential awareness that occurs in the impulsive system, noetic awareness happens in the reflective, deliberative system and "consists of knowledge that something is or is not the case . . . [yet this might] be accompanied by an experiential state of awareness, which consists of a particular feeling" too (Strack and Deutsch, 2004, p. 225).

Consumer behavior research has focused on identifying reasons for action, which have been studied by two somewhat distinct groups of researchers. For example, under the broad label of cognitive processes, one group of researchers devotes much energy to such processes as attention, perception, categorization, schemas, memory, inferences, and information search (e.g., Bagozzi, Gürhan-Canli, and Priester, 2002, pp. 130–168). A second group of researchers investigates fewer reasons for action than the first group and is largely concerned with summary evaluative and judgmental reactions and their implications. The foundation for this research can be found in the "attitude tradition," which began in earnest with Triandis (1977), Fishbein and Ajzen (1975), and Ajzen and Fishbein (1980) (also see Bagozzi, Gürhan-Canli, and Priester, 2002, pp. 1–129). Research in the cognitive processes tradition has attempted to understand the bases for attitudes, intentions, and related phenomena, whereas the attitude tradition has only occasionally been concerned with these issues but rather has been more interested in the implications of attitudes, subjective norms, and so on. Neither tradition has specified how actions are produced, and neither tradition has investigated the theoretical mechanisms linking the bases for action to motivation and decisions to act. We turn now to these issues.

### *The CIAD Model*

Most research in the consumer behavior and consumer attitude traditions rests on the assumption that the reasons for action—cognitive responses, attitudes, subjective norms, and so on—causally influence decisions and intentions. I argue that the logic for such a causal relationship is typically lacking in that the motivation to act is frequently missing when one cognitively responds one way or the other, has a favorable or unfavorable attitude, and so forth. The motivational content results, if it results at all, it is claimed, only after a process of reasoning transpires, whereby a decision maker first considers–imagines–appraises–decides (CIAD) in relation to perceived reasons for acting (see below), and then the desire (lack of desire) resulting therein influences (fails to influence) a decision or intention. In other words, active processing of reasons to act is transformed into desires to act. (I reiterate here that I am speaking about the deliberative system; the impulsive system obviously functions differently as discussed above.)

The CIAD transformation process functions as follows. A decision maker first *considers* a goal in the sense of becoming aware of an opportunity, being assigned the goal as part of one's role in a group or organization, or reconsidering a previously held goal. Next, the decision maker vividly *imagines* achieving and failing to achieve the goal and elaborates on the meaning and implications of the goal, goal striving, and goal achievement/goal failure for him- or herself personally. We will describe an example of such processes, termed *prefactual thinking*, in our later discussion of anticipated emotions. Then the meaning of the goal-striving process and imagined outcomes of goal success and failure are *appraised* for personal relevance. This is done along with the imagining processes, and indeed consideration, imagining, and appraisal are complexly intertwined and difficult to separate. Note that appraisals need not be done consciously but can be automatic and unconscious. The outcome is a transformation of reasons for accepting a goal or reasons for acting into motives for acting, wherein one *decides* to accept the goal or motive as a basis for acting. That is, the decision maker becomes aware of his or her felt desires with respect to a goal or action and accepts these as personally relevant criteria for committing to a goal or acting to achieve a goal. A final step is required wherein multiple recognized personal wants or desires are integrated into an overall desire to accept a goal or not or to act or not in goal pursuit. This issue will be discussed later in this chapter, in the section Desires to Act.

I am suggesting that there are two dual reflective, deliberative processes. One is the commonly assumed passive functioning of attitudes and similar reasons for acting. Here attitudes, to take an example, are relatively stable evaluative responses that are learned and become predispositions to respond in subsequently experienced situations compatible with the attitude or its acquisition (Eagly and Chaiken, 1993). For classically construed attitudes to have an effect on intentions, say, they must be retrieved or activated from memory. But the theory behind their emotive effects on intention has not been developed, and therefore tests to date of the "effect" of attitudes rely on demonstrations of empirical associations between attitudes and intentions without investigation of the mechanism underlying the presumed causal process. An exception is the role of attitude in Fazio's MODE model, but here the effects occur in the impulsive system. The impulsive mechanism is typically not demonstrated in survey research that studies the effects of attitudes. Thus we are often left without a firm basis for interpreting observed associations between attitudes and either intentions or behavior as causal relations in such research.

The other reflective, deliberative process I am suggesting is an active one entailed by the processes in the CIAD model. Here reasons for acting are considered dynamically in a specific goal context as the decision maker becomes aware of them, and they are transformed into desires for a goal or desires to act, under the proper conditions. Following this, multiple desires are reconciled and integrated into an overall desire, which becomes the emotive explanation for intention formation.

### *Goal Setting*

Gollwitzer (1990) characterizes goal setting as engagement in the appraisals of the feasibility and desirability of a candidate goal. This is a simple way to conceive of goal setting, yet very little research exists studying the phenomenon from this perspective (e.g., Bagozzi, Dholakia, and Basuroy, 2003; Perugini and Conner, 2000).

From a different perspective, my colleagues and I, as well as other researchers, have investigated goal setting as a response to multiple values or motives organized in a meaningful way (e.g., Bagozzi and Dabholkar, 1994, 2000; Bagozzi, Bergami, and Leone, 2003; Bagozzi and Edwards, 1998; Bagozzi, Henderson, Dabholkar, and Iacobucci, 1996; Pieters, Baumgartner, and Allen, 1995; Morandin, Bergami, and Bagozzi, 2005; Taylor et al., 2005a). Anthropologist D'Andrade succinctly summarizes the starting point of our perspective:

> To understand people one needs to understand what leads them to act as they do, and to understand what leads them to act as they do one needs to know their goals, and to understand their goals one must understand their overall interpretive system, part of which constitutes and interrelates these goals, and to understand their interpretive system—their schemas—one must understand something about the hierarchical relations among their schemas. (1992, p. 31)

In this research, values or motives for an adopted or potential goal are elicited in a way that reveals the interconnections among the values and motives. The bases for consumers' schemas are disclosed by asking them to first give their personal reasons (i.e., values, motives, subgoals) for pursuing a focal goal (or not), and then through a series of questions, justifications for each reason are obtained, explanations for the justifications recorded, and so on until no further unique explanatory responses result. The data so gathered are content analyzed to arrive at a common and manageable representation of decision criteria and espoused connections between criteria. This is done at the level of each decision maker, but in addition, a summary map of the hierarchical values, motives, or subgoals and their interrelationships for a sample of respondents is often derived for perspective. Hypotheses are tested at the levels of individual decision makers by showing the dependence of their global reasons for acting (e.g., attitudes, subjective norms, perceived behavioral control) on their individual values, motives, or subgoals and their expressed relationships among these values, motives, or subgoals. Regression analysis (e.g., Bagozzi and Edwards, 1998; Bagozzi, Bergami, and Leone, 2003) and *t*-tests (Taylor et al., 2005a) have been used to date in this regard.

This approach to goal setting, which we will call the *goal schema framework* for purposes of discussion, has a number of advantages over the more commonly used expectancy-value model (Bagozzi, Bergami, and Leone, 2003). The expectancy-value model presumes that the criteria people employ in decision making (which are termed beliefs or expectancies in the model) are weighted by evaluations of the criteria, and the products of beliefs and evaluations are summed to yield a single number for each person to represent his or her overall expectancy-value score. The goal schema framework has the advantage of representing hierarchies or complex patterns of the criteria upon which goal setting is based and can uncover the differential influence of specific subsets of the criteria on decision making, whereas the expectancy-value model focuses in its classical aggregative form on an overall prediction without attention given to specific, differential roles for beliefs and evaluations. Another advantage of the goal schema framework is that dependencies among criteria can be modeled so that the inferences implied by these dependencies can become independent variables predicting decision outcomes. Some beliefs, for example, are more vulnerable to change efforts, other beliefs are more efficacious, and still other beliefs are more ethical to target than others. The expectancy-value model ignores or confounds relationships, if any, among beliefs in its format. Finally, the expectancy-value model, whether tested in its standard aggregate formulation or a disaggregated version, requires that either ratio scaled measures be used, or if interval or ordinal measures are employed, additive effects must be controlled for in tests of the primary multiplicative effects, which create operational difficulties. The goal schema framework can be tested with less restrictive statistical methods.

The primary value of the goal schema framework is to identify possible values, motives, or subgoals and relations among these that then influence attitudes, subjective norms, and analogous molar representations of the reasons for acting. The goal schema framework is thus a preliminary step for identifying antecedents to reasons for acting that must be formally tested in subsequent research.

### *Attitudes*

Attitudes are central determinants of intentions in the TPB and TRA, along with subjective norms and in the case of the TPB, also along with perceived behavioral control. The TPB and TRA are basically deliberative frameworks, but as noted earlier recent work on implicit attitudes and a portion of Fazio's (1990) MODE model suggest that attitudes can function in automatic, impulsive ways as well.

Figure 1.2 summarizes how attitudes, subjective norms, and perceived behavioral control have been shown recently to function in a deliberative sense within the context of an expanded model of consumer action (e.g., Bagozzi, Dholakia, and Basuroy, 2003; Taylor, Bagozzi, Gaither, and Jamerson, 2005b). Attitude here is represented as a singular attitude toward the act under consideration.

Recent research has shown that attitudes may be reconceptualized as multidimensional evaluative and/or affective responses. One approach is to construe attitudes toward an act in separate affective and cognitive components (e.g., Bagozzi, Lee, and Van Loo, 2001); another approach is to represent attitudes in goal-contexts in three separate components: attitudes towards success, failure, and the process of goal pursuit (e.g., Bagozzi and Warshaw, 1990; Bagozzi and Kimmel, 1995; Bagozzi, Moore, and Leone, 2004). A fuller presentation on the nature and operation of multidimensional attitudes can be found in Bagozzi (2005) and Bagozzi, Gürhan-Canli, and Priester (2002).

Multidimensional attitudes are not depicted in Figure 1.2 because, especially for the representation of attitudes toward success, failure, and process, these constitute alternatives to the effects of anticipated and anticipatory emotions, which are shown in Figure 1.2 and will be discussed in the following two subsections. However, it should be noted that attitudes toward the act, which differ fundamentally from attitudes toward success, failure, and process (see under the next subsection, Anticipated Emotions, and Bagozzi, Moore, and Leone, 2004, p. 203), have been found in recent research to contribute to decision making independently of anticipated emotions (e.g., Bagozzi and Dholakia, 2005a, b; Perugini and Bagozzi, 2001; Taylor, Bagozzi, Gaither, and Jamerson, 2005b).

A final point that can be made with respect to attitudes is that these responses have been shown to be dependent on anticipated emotions, as moderated by regulatory focus. Leone, Perugini, and Bagozzi (2005) showed that anticipated agitation emotions (nervous, agitated, anxious, anguished) induce more favorable evaluations to act under a prevention focus (i.e., the chronic strategic orientation to seek security and avoid punishment and negative outcomes), whereas anticipated dejection emotions (dissatisfied, ashamed, sad, unworthy) lead to more favorable evaluations to act under a promotion focus (i.e., the chronic strategic orientation to seek opportunities for reward and positive outcomes). This shows that an individual difference, regulatory focus (e.g., Higgins, 1998), controls the effects of anticipated emotions on attitudes. This is a third way that attitudes can be influenced, in addition to the information-based approach of the expectancy-value model and the values, motives, or subgoals-based approach of the goal-schema framework.

### *Anticipated Emotions*

Attitudes are predispositions to respond in a favorable or unfavorable way to an object or action (e.g., Campbell, 1963). Typically, attitudes arise through learning, whereby a person acquires a reaction to an object or action over a period of time through repeated contact accompanied by reinforcement. An attitude is an evaluative response that, when learned, is triggered automatically when one is exposed to the object or act or thinks about it (Fazio, 1995). In this sense, attitudes are reactive and passive.

A more dynamic and self-regulatory way of acting has been proposed through the operation of *anticipated emotions* (AEs). Bagozzi, Baumgartner, and Pieters (1998; see also Bagozzi, Baumgartner, and Pieters, 2000; Bagozzi, Gürhan-Canli, and Priester, 2002, pp. 90–104) proposed that people consider the prospects of both goal success and goal failure by "imagining the possible" (i.e., identifying and appraising the consequences occurring if one were to achieve one's goal *and* fail to achieve one's goal). The decision maker generates alternative consequences to imagined goal success and goal failure, which then serve as input for appraisals and the generation of anticipated emotional responses. The thought processes entail a type of forward-looking counterfactual thinking. By imagining what would happen if one succeeded and if one failed to achieve a personal goal, a decision maker elaborates upon the goal situation and sets the stage for emotional appraisals. Note that appraisals need not be, and often are not, deliberative but can be automatic. But the "consider, imagine, and decide" phases of the process are deliberative. Imagined goal success generates such positive emotions as excitement, happiness, and pride; imagined goal failure engenders such negative emotions as anger, disappointment, and sadness.

Frijda (1986, p. 98) argued that emotions are defined by an intentional structure and that these intentional structures are "engendered as part of the plan to fulfill a given action tendency." Furthermore, although he did not discuss the issue in detail, Frijda (1986, p. 97) acknowledged the possibility that behavior "can be motivated by the anticipation of emotion that could or will occur," but "little systematic research exists on the actual relationships between emotions and corresponding changes in . . . goal-directed behaviors" (Frijda, 1993, p. 393). Building in part on the cybernetic theory of control (e.g., Carver and Scheier, 1998), Bagozzi, Baumgartner, and Pieters (1998) hypothesized and found that (1) positive and negative AEs influenced volitions to act (i.e., intentions, plans, and anticipated expenditures of effort), (2) volitions led to the performance of goal-directed behaviors, (3) goal-directed behaviors determined the degree of goal attainment, and (4) the extent of goal attainment fed back on positive and negative emotions in a panel study of body weight regulation.

We suggest that AEs are not passive responses retrieved from memory, as are attitudes, but rather are dynamic constructions of how a decision maker feels about outcomes related to goal pursuit. The decision maker considers his or her goal, thinks about and imagines two aspects thereof (achieving and failing to achieve the goal), appraises the meaning of goal attainment and goal failure, experiences positive and negative emotions, and decides to act so as to fulfill goal achievement/avoid goal failure.

Anticipated emotions apply especially to situations in which consumers already have goal intentions. Positive and negative AEs capture a decision maker's appraisals of the significance of anticipated goal outcomes for his or her survival or for flourishing in a specific goal situation.

The emotions experienced thereof provide motivational bases for deciding to act so as to approach positive or pleasurable anticipated outcomes and to avoid negative or painful anticipated outcomes. Given a goal intention, the prefactual thought processes and appraisals underlying AEs function to translate the goal intention into an implementation intention. That is, favorable appraisals activate an implementation intention in the service of a previously formed intention to achieve a goal. Anticipated emotions might also initiate goal-setting processes and influence goal desires (Bagozzi, Dholakia, and Basuroy, 2003). See Figure 1.2.

Several studies have validated the role of AEs and have tested these processes within the context of the TPB or expanded theories: Bagozzi and Dholakia (2002; 2005a, b); Bagozzi, Dholakia, and Klein Pearo (2005); Bagozzi, Dholakia, and Mookerjee (2005); Brown, Cron, and Slocum (1997); Dholakia, Bagozzi, and Klein Pearo (2004); Perugini and Bagozzi (2001); Perugini and Conner (2000); and Taylor, Bagozzi, and Gaither (2005b). Depending on the circumstances, sometimes either positive AEs or negative AEs are efficacious; at other times both positive and negative AEs function as determinants of decision making. Again, it is important to point out as well that attitudes and AEs are different constructs and can have separate effects on decision making.

This raises the following question: What are the differences and similarities between attitudes and AEs? Note, too, that attitudes can be divided into passive (i.e., learned predispositions to respond in a favorable or unfavorable manner) and active (i.e., attitudes toward success, failure, and process) versions, where the latter show some similarity to, yet distinctions from, AEs. Active attitudes arise through similar prefactual thinking processes as AEs. One difference among passive attitudes, active attitudes, and AEs involves the general targets of each. Attitudes under the TPB refer to actions ($A_{act}$), active attitudes concern goals, and AEs also address goals. But the goals for active attitudes encompass outcomes (attitudes toward success and failure) and goal-directed behaviors (attitudes toward process), whereas goals for AEs involve only outcomes (success and failure). A second difference lies in dimensionality. The $A_{act}$ is unidimensional, active attitudes are three dimensional (attitudes toward success, failure, and process), and AEs are bidimensional (positive and negative AEs). Third, these three reasons for action differ in terms of formation and activation. The $A_{act}$ is a passive reaction, and its effects require retrieval from memory; it reflects prior learning and functions as a learned disposition. Active attitudes and AEs are dynamic in the sense of arising from thinking and appraisal processes at the time of decision making and involve forward-looking judgments and feelings; they change as the contingencies and value of goals and their attainment change. Fourth, $A_{act}$ and active attitudes are evaluations; AEs are affective processes. Fifth, $A_{act}$ and active attitudes are measured as bipolar semantic differential items, whereas AEs are measured as unipolar items (see Bagozzi, Wong, and Yi, 1999, for the implications of using bipolar versus unipolar items). Sixth, $A_{act}$ focuses on behaviors, but the behaviors are not specified within the TPB to pertain explicitly to a goal held by the decision maker; active attitudes and AEs specifically apply to the case in which a goal intention has been formed and the attitudes and emotions function to activate an implementation intention in order to fulfill the goal intention. Nevertheless, AEs can initiate goal-setting processes and influence goal desires (Bagozzi, Dholakia, and Basuroy, 2003).

### *Anticipatory Emotions*

Emotions experienced in anticipation of imagined future goal success/failure are termed *anticipated emotions.* They refer to prefactual judgments about how one would feel in future situations, after something desired happens or does not happen. As such, nearly any positive or negative emotion can function as an anticipated emotion. In and of themselves, anticipated emotions are not formed under conditions of uncertainty. Indeed, given the mental simulation of imagined success/failure, they are presumed to occur with certainty, whether or not the goal is attained.

Another kind of future-directed emotion is the *anticipatory emotion,* which also can be positive and negative. Anticipatory emotions are presently felt emotional responses to the prospect of a desired/undesired future event. Unlike anticipated emotions, anticipatory emotions are restricted to two subcategories within the categories of positive and negative emotions. That is, hope and fear are the prototypically felt anticipatory emotions. A defining characteristic of anticipatory emotions is their dependence on the probability of an event happening. Hope and fear, and their cognates, are intimately bound or endogenous to certainty/uncertainty of an event. The probability of the occurrence of an event, such as goal attainment or goal failure, with respect to anticipated emotions, is exogenous to the felt emotions and can be incorporated in models of consumer behavior as expectations of success and expectations of failure (e.g., Bagozzi and Warshaw, 1990; Bagozzi and Kimmel, 1995). Both anticipated and anticipatory emotions have motivational implications.

Baumgartner, Pieters, and Bagozzi (2004) investigated the measurement properties and functioning of both anticipated and anticipatory emotions in a study of decision making by people preparing for the millennium. Measures of positive and negative anticipated and anticipatory emotions achieved convergent and discriminant validity. Interestingly, positive and negative anticipated and negative anticipatory emotions all affected intentions to do or not do various things in order to avoid or limit the possible negative consequences of the millennium problem; intentions fully mediated the effects of positive and negative anticipated and anticipatory emotions, as well as future anxiety and judged probability of negative consequences on actual action taken. Further research is needed into the conditions governing the functioning of anticipated and anticipatory emotions, the relative contribution of these emotions vis-à-vis attitudes and other reasons for acting, and the role of (first-order) desires as mediating variables and second-order desires as moderators (see the next major section).

### *Additional Reasons for Action*

The TPB, TRA, and similar approaches neglect considering important reasons for action. To make the role of AEs more complete, for example, it would seem desirable to add affect toward the means of goal striving as an antecedent to decision making. This has not been done before, yet affect toward the means has been shown to be important reasons for action (Bagozzi, Baumgartner, and Yi, 1992; Bagozzi and Edwards, 2000), and has similarities (but with the differences implied previously) with attitude to the process of goal pursuit discussed above. Note that affect toward the means and attitude toward the process of goal pursuit are distinct from the positive and negative affect arising from appraisals of progress made in goal striving, which moderates the relationship between trying and goal achievement/failure (see Figure 1.2). Another need regarding specification of reasons for action is for incorporation of social processes. Presently, subjective norms constitute the only variables containing social content in the TPB and TRA, but subjective norms often fail to predict intentions in empirical work, due, in part, to the restricted domain of social action they represent. I return to this issue subsequently in the section titled Consumer Self-Regulation, where social identity and the social and self-conscious emotions are considered. The TRA and TPB also do not accommodate social phenomena in the form of group normative influence (see Bagozzi and Lee, 2002). Finally, the TRA and TPB fail to take into account emotion, desire, volition, and both planning and related postintention processes.

**Desires to Act**

Many reasons for action by themselves lack motivational content and impetus for taking an action or even for making a decision to act one way or the other. A favorable attitude can, for example, lead to a decision to act under the right conditions, but in and of itself, an attitude need not causally contribute to intention formation. A person can have a favorable attitude toward an object or act, yet not feel a desire to act or be committed to acting. Indeed, a favorable attitude need not function even as a motivation to act. Similar comments apply for the potential effects of subjective norms, perceived behavioral control, and many other reasons for action based on beliefs or cognitive responses.

The following question arises, then: How do reasons for action translate or become transformed into decisions to act, trying, and action? Bagozzi (1992, pp. 183–194) proposed that *desires* are fundamental psychological events or states (distinct from the reasons for action noted previously) that are necessary for converting reasons for action into intentions to act. In other words, desires mediate the effects of reasons for action on intentions to act. These desires might be termed *behavioral desires* because they refer to the desire to act. Another form of desire is the goal desire (the desire to achieve a goal), which is a precursor to goal intentions. Mele (1995) terms the former extrinsic desires (desiring to act as a means to an end) and the latter intrinsic desires (desiring something for its own sake or as an end). See Figure 1.2.

To see better what desires are, it is helpful to distinguish between volitive and appetitive desires. Davis (1997, p. 136) notes that a volitive desire is "synonymous with *want, wish,* and *would like,* and appears as a *transitive verb* in sentences like 'I desire to . . .' and 'I desire . . .' " (emphasis in original). For example, "John would like to exercise" and "Mary wants intellectual stimulation" are volitive desires. In contrast, an appetitive desire has "the near synonyms *appetite, hungering, craving, yearning, longing,* and *urge,* and appears as a *noun* in sentences like 'I have a desire to . . .' and 'I have a desire for . . .', [moreover,] objects of appetitive desire are *appealing,* things we *view with pleasure*" (Davis, 1997, p. 136, emphasis in original). For example, "Silvia has a longing to visit her birthplace" and "Paul has a craving for sushi" are appetitive desires. Davis points out that volitive and appetitive desires are logically independent and can exist empirically in distinct ways:

> We often want to eat, for social or nutritional reasons, when we have no appetite and view the prospect of eating without pleasure. We desire to eat, but have no desire to. On the other hand we may have a ravenous appetite and find the prospect of eating terribly appealing and yet not want to eat because we are on a diet. (1997, p. 136)

Nevertheless, Davis (1997) notes that appetitive and volitive desires can coincide, or in other cases the former sometimes leads to the latter.

What do desires do and how do they function? Desires serve a motivational function; they motivate our goal intentions and our behavioral intentions. One way they do so is automatically and nonconsciously. Damasio (1994, pp. 173–174) maintains that prior to the conscious processing of pros and cons characteristic of rational decision making, people experience pleasant or unpleasant feelings that highlight options and create either positive or negative biases, which favor or eliminate options from consideration (see also Damasio, 1999). Damasio termed this the *somatic-marker hypothesis*. We suggest that such unconscious processes influence or bias a number of antecedents to decision making and indeed can form the basis for certain desires. We might speculate that declarative knowledge processed rationally by consumers (with regard to facts, alternative goals and brands, consequences of consumption, and various expectations one has) is influenced by unconscious preference biases residing in the brain and arising from previous emotional experience associated with similar decision problems. Bechara and colleagues (1997) present research showing that such covert processes bias decision making prior to cognitive evaluation and reasoning and without awareness occurring on the part of decision makers. The authors suggested that the unconscious processes guide or shape behavior, before conscious processing commences, and function to produce better decisions, especially to the extent that learning accumulates as a consequence of previous rewards and punishments, which become stored as nondeclarative dispositional knowledge. Earlier we discussed other automatic processes and how they interact with deliberative processes. It is possible that some desires, especially appetitive ones, develop in this way and become the basis for goal desires and even some behavioral desires.

People are often aware of their desires, and desires seem to function consciously in many decision-making settings. This is especially true for volitive desires. It is common for a decision maker to have many reasons for action, some of which might even conflict or constitute reasons for not acting in the very same decision context. In such cases, desires serve to integrate or summarize a decision maker's overall felt urge to act as a function of multiple reasons for action. Reasons for action are appraised, combined, and transformed into a motivation to act. Whether this happens as a deterministic resultant of competing forces in response to reasons for action, or follows learned rules of weighting and consolidation, remains to be studied. But in the face of multiple reasons for acting and not acting, in which some reasons are determinative whereas others are not, people can subjectively experience and express their final felt urge to act.

A third function for desires is to induce an intention; a goal desire incites a goal intention, and a behavioral desire evokes an implementation intention. Desires harbor energy in an action-tendency or consummatory sense, but without precise direction and without a personal commitment to act. Intentions provide precise direction and personal commitment in this sense. These are the primary differences between desires and intentions. Yet another distinction is that intentions, but not desires, can entail a plan to act (Bratman, 1987), though not all intentions necessarily contain or imply plans. Perugini and Bagozzi (2004b) explored additional distinctions between desires and intentions (see also Perugini and Bagozzi, 2004a).

Recently, the role of desires in sequential impulsive choices has been investigated. Dholakia, Gopinath, and Bagozzi (2005) found that desires for impulsive products function as limited motivational resources in the sense that consumption of a product purchased impulsively in one task can lead to a reduction in desires for subsequent impulsive choice opportunities for other products. In one experiment, the decision maker's chronic sensitivity to positive and negative outcomes was shown to moderate the observed decrement in desires from one impulsive choice to another. Ongoing research investigates the mechanism behind these effects, including the possibility that self-esteem and positive feedback function to regulate one's indulgences.

A growing body of research has confirmed the transformative and mediating role of desires: Bagozzi and Dholakia (2002, 2005a, b); Bagozzi, Dholakia, and Basuroy (2003); Bagozzi, Dholakia, and Klein Pearo (2005); Bagozzi, Dholakia, and Mookerjee (2005); Bagozzi and Edwards (1998); Bagozzi and Kimmel (1995); Dholakia, Bagozzi, and Klein Pearo (2004); Perugini and Bagozzi (2001); Perugini and Conner (2000); and Taylor, Bagozzi, and Gaither (2001, 2005b).

Some refinements in the functioning of desires are in need of further work. Although it is clear that evaluations and beliefs lack motivational content, in and of themselves, and therefore must work through desires if they are to instigate action, AEs can contain sufficient motivational force to influence intentions directly. Research is needed into the conditions when AEs directly influence intentions and when they indirectly influence intentions through desires. Similarly, desires might have nonderivative effects on intentions. For example, appetitive desires do not depend typically on reasons for action (though it is possible for reasons to "free up" a latent appetitive desire), and as a consequence appetitive desires might influence an intention autonomously or even directly influence action if strong enough or activated in the impulsive system. Researchers need to study the conditions governing the nonderivative effects of appetitive desires versus the derivative effects of volitive desires.

## Consumer Self-Regulation

Self-regulation has been defined as "any efforts by the human self to alter any of its own inner states or responses" (Vohs and Baumeister, 2004, p. 2) and is often used interchangeably with self-control. However, it can be argued that much research falling under the label "self-regulation" or "self-control" (e.g., Baumeister and Vohs, 2004; Carver and Scheier, 1998; Higgins, 1997) is not self-regulatory in a strict sense and in fact represents variants of deterministic processes but without what we might term *free will*.

Free will is a very difficult to understand, long-standing, and controversial topic in philosophy, and it would be impossible to do it justice here. Free will involves complex issues of compatibilism versus incompatibilism, determinism versus indeterminism, and many special cases and variants of these ideas (for a selective coverage of the issues, see Benn, 1988; Berofsky, 1987; Bishop, 1989; Double, 1996; Ekstrom, 2000; Fischer, 1994; Kane, 1996; Smilansky, 2000; Swanton, 1992; Williams, 1980). As a loose-working definition to set the stage for what is to follow, we adopt the position that "'free will' is the conventional name of a topic that is best discussed without reference to the will, per se. Its central questions are 'what is it to act (or choose) freely?' and 'what is it to be morally responsible for one's actions (or choices)?'" (*Concise Routledge Encyclopedia of Philosophy,* 2000, pp. 293–294). In their hypotheses and empirical work, social psychologists implicitly assume what might be termed compatibilism in that all the variables and processes in their theories operate deterministically (i.e., situational and individual difference variables affect information processing, and action is directly dependent on the outcome of the processing, which itself is deterministically explained, yet people are not forced to act by compulsion). But what is missing from social psychological theories of self-regulation is how acting freely and doing so in a morally responsible or caring way are compatible with the idea of determinism.

The approach taken by Bagozzi, Gürhan-Canli, and Priester (2002, pp. 81, 98, 174) builds on Frankfurt's (1971, 1988) notion of second-order desires. Frankfurt (p. 1971, p. 7) suggested that people have the capacity for reflective self-evaluation such that they can become aware of their motives, feelings, beliefs, and (first-order) desires. People, to different degrees, also have the capacity to evaluate their (first-order) desires and decide whether they want to have or want to not have the desires that they experience and scrutinize. Frankfurt (1971) termed the latter *second-order desires,* and I retain this label herein. However, I wish to construe second-order desires in a somewhat different and fuller way than Frankfurt originally proposed (1971, 1988). I suggest that a decision maker can come to reflect upon a felt desire to act (or to have a goal desire) in such a way as to cancel, override, or postpone further consideration or implementation of the desire to act. More specifically, I propose that, when thinking about one's desire to act (or one's goal desire), a person asks him- or herself such questions as the following:

- Am I the kind of person who should have such a desire?
- Am I the kind of person who acts on this kind of desire?
- Is the desire that I feel consistent with the kind of person I wish to be?
- Will acting on this desire lead to personal flourishing?
- What effect will acting on this desire have on other people important to me, other people whom I may not even know, or social welfare writ large?

In a parallel manner, I propose that a decision maker can reflect upon his or her lack of a felt desire for a goal or to act. Here the person considers whether to accept, embrace, or construct a desire for a goal or to act; questions analogous to those noted previously could be posed self-reflectively (e.g., "Is my not feeling a desire to act consistent with the type of person I wish to be?").

Second-order desires, then, constitute self-regulatory expressions of one's will. I hypothesize that they moderate (i.e., interact with) the effect of first-order desires on intentions. The second-order desires are personal self-evaluative or moral standards concerning who a person is or wants to be. They either confirm or conflict with one's first-order desires and then function to facilitate or stop the effect of the desire on intentions. Second-order desires also can produce creatively a first-order desire where none previously existed. Note that second-order desires interact with goal desires to regulate goal intentions, and they interact with behavioral desires to regulate implementation desires (see Figure 1.2). No empirical research could be found testing the aforementioned moderating role of second-order desires. This is an important opportunity for future research!

To the best of my knowledge, neither Frankfurt nor other authors have given much attention to the question of how second-order desires arise in the first place. Based on emerging research in emotion psychology and organizational studies, I suggest that second-order desires arise from or are influenced by three broad social psychological forces: self-conscious emotions, social identity, and caring, love, or empathy for people, animals, nature, ideals, and perhaps even the self (see Figure 1.2).

### *Self-Conscious Emotions*

Self-conscious (SC) emotions emerge when a person's "I" (oneself as an active agent) reflects on and becomes conscious of his or her "me" (one's categorical or social self). Under this process, the "I" takes the "me" as an object of self-reflection and self-evaluation (e.g., Harter, 1999). SC-emotions function as people's situational sensors to scrutinize whether *they* or *their behaviors, goals,* or *desires* fit a significant social group or particular social setting based on evaluative signals from members of the target group or setting (e.g., Fischer and Tangney, 1995; Lewis, 2000). Baumeister (1995) suggests that people constantly have a need to monitor and assess whether they belong to and are accepted by members of their significant social group. The need to belong causes consumers to pay attention to positive and negative evaluations from others and to learn about the values and norms that are typical for a particular group. Depending on the nature of the evaluations and their importance, consumers will be motivated to change their goals, decisions, or behaviors. I suggest also that SC emotions sometimes become internalized, such that consumers need not be aware of specific groups, per se, when they experience these emotions. SC emotions shape, instigate, or condition second-order desires. They also play a role in the developing of second-order desires, especially as grounded in early life experiences.

Common examples of SC emotions include pride, shame, embarrassment, guilt, envy, and jealousy. In addition, empathy and social anxiety sometimes function as SC emotions. SC emotions have been little studied in consumer research. For SC-emotion research in the related area of salesforce behavior, see Bagozzi, Belschak, Verbeke, and Gavino (2004); Bagozzi, Verbeke, and Gavino (2003); Belschak, Verbeke, and Bagozzi (2005); Verbeke and Bagozzi (2000, 2002, 2003); and Verbeke, Belschak, and Bagozzi (2004).

### *Social Identity*

People belong to groups, and this membership has profound effects on their practical decision making and what they care about. Bergami and Bagozzi (2000) identified three aspects of group membership that constitute one's social identity: (1) awareness of own group membership, which entails cognitive self-categorization processes; (2) affective commitment, which includes emotional feelings of belongingness and attachment to a group; and (3) positive or negative value connotations of group membership, which has been termed collective self-esteem. Social identity in this tripartite sense has been shown to affect first-order desires (e.g., Bagozzi and Dholakia, 2002, 2005a, b; Bagozzi, Dholakia, and Klein Pearo, 2005; Dholakia, Bagozzi and Klein Pearo, 2004; Bagozzi and Lee, 2002). This is shown as a dashed arrow in Figure 1.2. However, I submit that the effect of social identity is often indirect; it influences second-order desires, which in turn, moderate the impact of first-order desires on intentions.

### *Caring, Love, Empathy*

The moral and self-evaluative standards that we use as self-regulative mechanisms, and more generally, our second-order desires, seem to be shaped by what we care about deeply or the love we have for another person, friends, a larger community, one's God or deity if one is religious, and even oneself (the latter not in a self-indulgent or selfish way but rather in relation to another person or something else one cares about). Frankfurt (1988) has explored some of the issues here, but not much by way of development of a theory of second-order desires and their determinants has been proposed. For now, we leave for further consideration how caring, love, and concern or empathy for various targets come to shape our moral and self-evaluative standards and more generally our second-order desires.

## Conclusion

Consumer action occurs in response to automatic and deliberative processes and is controlled by consumer agency through self-regulatory functions. The possibility exists as well that consumers initiate action in a personally autonomous way. This might occur through an overriding of inhibitions to act or the self-formation of desires to act in a manner deemed consistent with the kind of person one is or wants to be or conducive to personal flourishing.

Automatic, deliberative, and self-regulative systems are constituted in large part by evaluation, motivation, and emotion, in addition to the obvious cognitive responses so frequently studied to date. These processes function in multiple places and at multiple stages of decision making. They interpret the relevance of things happening to consumers, motivate information processing and action, reconcile the relationships consumers have with other people, institutions, and their own value systems and codes of conduct, control the direction and magnitude of effort expended in goal pursuit, and initiate and terminate action. Some evaluative and emotive processes are automatic in that they are either hard-wired so to speak or learned through repeated performances under particular conditions of reinforcement or other learning mechanisms. Many evaluative and emotive processes are deliberative as well.

Evaluative and emotional processes can be seen at various places in Figure 1.2. The desire to pursue a goal is influenced directly by anticipated and anticipatory emotions and by affect toward the means of goal pursuit. Motivation to act is reflected in goal desires and behavioral desires, which serve to summarize consumers' overall urges to pursue goals and act instrumentally to do so, respectively. Goal and behavioral intentions are under the direct influence of goal and behavioral desires. At the same time, depending on the outcome of human developmental processes and socialization, moral and self-evaluative standards moderate the effects of desires on intentions. These standards are in turn shaped by a number of evaluative and emotional processes. Social and self-conscious emotions function to promote or inhibit the application of personal standards to the regulation of desires. Affective and evaluative commitments to organizations or groups also influence personal standards, as do the caring, love, or empathy consumers exhibit for things and people they cherish. Finally, emotion functions to moderate the effects of trying on goal attainment, as progress waxes and wanes and plans are fulfilled or blocked.

To be clear, I stress that emotions are not something to be denied or avoided. Ancient Stoics and Cynics promoted a view where the ideal was "freedom from passions" (i.e., apotheia; see Epictetus, 1995). By contrast, I suggest that emotions are to be harnessed, coped with, and integrated into everyday decision making if consumers are to achieve their goals and flourish. To be sure, much of emotional life is automatic. But at the same time, we are able to self-regulate our emotions to a certain extent and influence the effects that they have on information processing, motivation, choice, and social life. Second-order desires and the social and self-conscious emotions play key roles here.

Cutting across a number of emotional processes in some sense, and standing alone in other senses, are social forces impinging on consumer action (e.g., Bagozzi, 2000b; Bagozzi and Lee, 2002; Bergami and Bagozzi, 2000; Dholakia, Bagozzi, and Klein Pearo, 2004). Interpersonal processes in the form of compliance are reflected in part in the operation of subjective norms. Internalization of norms and values from the groups to which one belongs is captured through the working of group norms. Identification with an organization or other social entity works through social identity. Some emotions arise and function explicitly as a result of the social relationships one has and serve to guide decision making, as well as automatic responses.

A pressing question in consumer research is how physiological processes, particularly those in the brain and central nervous system, influence consumer behavior and action. A lot has been learned in neuroscience in recent years about how rewards and punishments are processed and function (e.g., Gazzaninga, 2004; Kandel, Schwartz, and Jessell, 2000). A person's states of affairs from the inside and out are represented in the cortical sensing and cognitive systems, hypothalamus, amygdala, and elsewhere, and then rewarding or punishing information is categorized in the orbital frontal cortex and computations of the difference between expected and actual rewards are performed in the basal ganglia; the control of responses to punishment is thought to occur in the dorsal raphe nucleus (DRN). The release of dopamine occurs in response to signals from the basal ganglia and is housed in the ventral tegmental area, whereas the release of serotonin occurs in the DRN. These, in turn, influence cortical areas responsible for trying to act and stored intentions, as well as such subcortical areas as the motor striatum, globus pallidus, and substantia nigra pars reticulate. Subparts of the cortical and subcortical systems then influence motor responses/functions in the motor anterior cingulated, motor prefrontal cortex, and the supplementary motor area. The cerebellum coordinates multiple motor responses and communicates with the supplemental motor area and the skeletal muscles. These are obviously complex responses, but we are learning much about the way rewards and punishments operate both automatically and deliberatively in the brain. This is a new frontier for consumer research.

The present chapter by design and necessity emphasized conceptual issues and attempted to put forth a prospectus for studying consumer action, while making links to past and ongoing research in these respects wherever possible. But it is important to once again stress that intimate and holistic relationships exist among theory, method, observation, and interpretation. One theme in this regard that I was not able to elaborate upon herein is the role of measurement, especially as it concerns the elicitation of self-reports. Underlying much of my research in recent years has been an attempt to ground the questions I ask of participants in my studies with a language that is simple and as universal as possible. This has meant utilization of basic concepts in queries that are tied to and elicit human thoughts and feelings that cannot be decomposed into simpler building blocks so to speak. This includes the use of such words as "do," "happen," "think," "know," "want," "feel," "true," "good," "bad," "now," "like" (to suggest similarity), "have," "can," and various quantifiers, intensifiers, and logical expressions, among other basic and, I hope, universal concepts. Although I have not fully succeeded in avoiding metaphors, higher-order concepts, and culture-bound words in my dialogues with participants, I have benefited greatly from ideas in contemporary linguistic research (e.g., Goddard, 1998; Wierzbicka, 1996). Wierzbicka (1996), for example, identifies more than 60 universal basic concepts that have emerged from her empirical cross-linguistic studies. To the extent that my measures of the variables and phenomena sketched in Figure 1.2 have succeeded, I attribute whatever empirical accomplishments that have occurred, in part, to the art of question design, as informed by modern linguistic principles and a growing personal sensitivity to the meaning of the words and responses used or produced by respondents across different cultures.

Another key issue for the future concerns the relationship between mental representations and events, on the one hand, and both measurements of these events and neural processes, on the other hand. These are not only scientific issues but philosophical ones as well. To put the approach advocated in this paper in perspective, I make the following comments as tentative commitments. First, I reject epiphenomenalism ,which considers mental events to be outcomes of physical processes but to have no causal relationship among themselves; I reject behaviorism, which places no credence on mental phenomena but rather focuses upon physical phenomena alone; I reject idealism, which is nearly the opposite of behaviorism in that there are believed to be only mental phenomena and the material world does not exist; likewise, I reject eliminativism, which also asserts that mental phenomena do not exist; I reject parallelism, which claims that mental events are linked between themselves, but no connections exist between the mental and the material; I reject occasionalism, whereby mental and material events are believed to covary, but have no causal linkages among them, because they have a common cause that controls everything; and I reject the identity theory, which asserts that mental events are identical with material events.

Second, the approach I favor, and one that is still in process of development, shares some aspects with (a) functionalism, which recognizes mental and material phenomena, while allowing for connections among mental events and between the mental and material; (b) the approaches associated with propositional attitudes; and (c) the approaches that formally connect mental and material phenomena by use of such frameworks as supervenience (although my interpretation of supervenience differs from leading expositions in certain respects, e.g., Kim, 1990). My approach is a realist one that accepts the proposition that mental events influence other mental events and are affected by and lead to physical events.

I have used the shorthand to refer to the various approaches and "isms" mentioned above to communicate to those who are already familiar with these terms; for newcomers who desire brief summaries of the various approaches, I recommend such sources as Audi (1995), Blackburn (1994), Honderich (1995), and the *Concise Routledge Encyclopedia of Philosophy* (2000). My expositions are too abbreviated and risk misrepresenting the underlying theses behind them, but this was necessary given the current venue and purpose of this chapter. My approach is not a purely causal one in the traditional sense, although much of a causal orientation will suffice to model the automatic and deliberative processes described herein. Nevertheless, as I have argued throughout, consumer action is not merely a response to things that happen to or in us, but rather involves human agency and self-regulation whereby people reflect upon how they feel and think and who they are or desire to be, and decide to act or not accordingly.

## Future Research

This chapter implies that there are a multitude of avenues for future research. First, it seems clear that there are numerous opportunities for original and applied research in the information processing tradition to study postdecision/postintention stages of consumer action initiation. There research might address planning, implementing decisions, monitoring progress in goal striving, resisting temptation and overcoming impediments to goal attainment, and reassessing and changing one's goals, plans, and efforts in goal pursuit, if warranted. Second, the nature and function of motivation deserves more scrutiny because cognitive processes provide only a partial perspective on consumer action and the impetus for action is little understood. Third, emotions play multifaceted roles at multiple stages of decision making and goal striving but are only now beginning to be investigated. Fourth, the personal and social identities of consumers should be scrutinized, for they do much to change consumer goals and actions. Fifth, much work is needed into consumer agency and how self-regulation occurs in consumption. Sixth, the neuroscience of information processing, motivation, and emotional responding in consumer research has received little effort to date. Difficult philosophical, conceptual, and methodological must be addressed in this area. Seventh, special inquiry seems needed into the linkage between instrumental acts and goal attainment. Eighth, the role of habitual and compulsive processes in consumption remains an underdeveloped area for inquiry. Ninth, the interaction between the deliberative and impulsive systems should be investigated. Tenth, conceptual work and hypothesis development are needed with regard to such concepts/processes as volition, intention, conation, trying, and self-control. Eleventh, the specification of dual processes is ripe for study. Twelfth, special consideration of first- and second-order desires in consumer decision making and action would help us bridge the cognitive processes and goal attainment gap that now exists in the field. Here, too, more attention to conceptualization, functioning, and measurement issues is needed. Finally, new methods of inquiry and of integrating existing methods may be needed to investigate consumer action fruitfully. Efforts at spanning research traditions and paradigms are needed which will require new ways of thinking about and evaluating theories, methods, and findings.

## Acknowledgment

The author would like to thank Dr. Leona Tam and Dr. Marco Perugini for providing valuable input and criticism to an earlier draft.

## Notes

1. A propositional attitude is "a kind of state of mind" that expresses a relation between a person and a

proposition (e.g., Honderich, 1995; see also Audi, 1995, pp. 719–720; and the *Concise Routledge Encyclopedia of Philosophy*). More formally, "If a person x thinks that *p,* desires that *p,* believes that *p,* is angry that *p,* and so on, then he or she is described as having a propositional attitude to *p*" (Blackburn, 1994, p. 307). Notice that thoughts, desires, beliefs, emotions, hopes, and intentions can all be instances of propositional attitudes. Notice further that what psychologists and consumer researchers term *attitudes* are but one kind of propositional attitude. Furthermore, "attitudes" as studied by psychologists and consumer researchers are sometimes treated as philosophers treat them but sometimes in a different sense, as the following observation implies: "It [a propositional attitude] suggests that knowing what someone believes, etc. is a matter of identifying an abstract object of their thought, rather than understanding his or her orientation towards more worldly objects" (Blackburn, 1994, p. 307). Importantly, propositional attitudes "feature in a distinctive mode of explanation—of rational beings; one species of such explanation is of action" (Honderich, 1995, p. 724).

2. An older English translation of this sentence that perhaps helps one grasp the fundamental meaning of the quotation from a slightly different perspective is the following: "The origin of action—its efficient, not its final cause—is choice, and that of choice is desire and reasoning with a view to an end" (Aristotle, 1915).

3. Aristotle originally proposed that choice is a function of both desire and reasoning. I maintain this general dependence but, for reasons developed later in the chapter, I argue that the influence of reasons for action operates through desire, which is the proximal motivation for choices and decision making.

4. This rendition of consumer action applies to deliberative or reasoned action. As developed below, we will introduce the notion that action can also be activated automatically. The need for dual-process models of the sort proposed herein builds upon research done by Strack and Deutsch (2004), Smith and DeCoster (2000), and Wilson, Lindsey, and Schooler (2000).

5. The concept and measurement of intention proposed by Ajzen and Fishbein (e.g., 1980) also confound intention, per se, with behavioral expectation (e.g., Warshaw and Davis, 1985).

## References


Aarts, H., and A. Dijksterhuis. (2000) "Habits as Knowledge Structures: Automaticity in Goal-Directed Behavior." *Journal of Personality and Social Psychology,* 78, 53–63.

Ajzen, I. (1991) "The Theory of Planned Behaviour." *Organizational Behaviour and Human Decision Processes,* 50, 179–211.

———. (2001) "Nature and Operation of Attitudes." *Annual Review of Psychology,* 52, 27–58.

———. (2002a) "Attitudes." In *Encyclopedia of Psychological Assessment,* vol. 1, ed. R. Fernandez Gallesteros, pp. 110–115. London: Sage.

———. (2002b) "Residual Effects of Past on Later Behavior: Habituation and Reasoned Perspectives." *Personality and Social Psychology Review,* 6, 107–122.

Ajzen, I., and M. Fishbein. (1980) *Understanding Attitudes and Predicting Social Behaviour.* Englewood Cliffs, NJ: Prentice-Hall.

———. (2004) "The Influence of Attitudes on Behavior." In *Handbook of Attitudes and Attitude Change: Basic Principles,* ed. D. Albarracin, B.T. Johnson, and M.P. Zanna. Mahwah, NJ: Erlbaum.

Allport, G.W. (1947) "Scientific Models and Human Morals." *Psychological Review,* 54, 182–192.

Anscombe, G.E.M. (1963) *Intention,* 2d ed. Ithaca, NY: Cornell University Press.

Aristotle. (1915) *Nicomachean Ethics*. Trans. and ed. W. Ross. *The Works of Aristotle,* vol. 9. London: Oxford University Press.

———. (2000) *Nicomachean Ethics.* Trans. and ed. R. Crisp. Cambridge, UK: Cambridge University Press.

Armitage, C.J., and M. Conner. (2001) "Efficacy of the Theory of Planned Behavior: A Meta-analytic Review." *British Journal of Social Psychology,* 40, 471–500.

Audi, R. (1995) *The Cambridge Dictionary of Philosophy.* Cambridge: Cambridge University Press.

Bagozzi, R.P. (1981) "Attitudes, Intentions and Behavior: A Test of Some Key Hypotheses." *Journal of Personality and Social Psychology,* 41, 607–627.

———. (1992) "The Self-regulation of Attitudes, Intentions, and Behavior." *Social Psychology Quarterly,* 55, 178–204.

———. (2000a) "The Poverty of Economic Explanations of Consumption and an Action Theory Alternative." *Managerial and Decision Economics,* 21, 95–109.

———. (2000b) "On the Concept of Intentional Social Action in Consumer Behavior." *Journal of Consumer Research,* 27, 388–396.

———. (2005) "Consumer Action: The Role of Intentionality, Emotion, Sociality, and Agency." In *16th Paul D. Converse Symposium*, ed. A. Griffin and C.C. Otnes, pp. 2–28. Chicago: American Marketing Association.

Bagozzi, R.P., H. Baumgartner, and R. Pieters. (1998) "Goal-directed Emotions." *Cognition and Emotion,* 12, 1–26.

Bagozzi, R.P., H. Baumgartner, R. Pieters, and M. Zeelenberg. (2000) "The Role of Emotions in Goal-directed Behavior." In *The Why of Consumption: Contemporary Perspectives on Consumer Motives, Goals, and Desires,* ed. S. Ratneshwar, D.G. Mich, and C. Huffman, pp. 36–58. London: Routledge.

Bagozzi, R.P., H. Baumgartner, and Y. Yi. (1989) "An Investigation into the Role of Intentions as Mediators of the Attitude-Behavior Relationship." *Journal of Economic Psychology,* 10, 35–62.

———. (1992) "Appraisal Processes in the Enactment of Intentions to Use Coupons." *Psychology and Marketing,* 9, 469–486.

Bagozzi, R.P., F. Belschak, W. Verbeke, and J.C. Gavino, Jr. (2004) Cultural Differences in the Self-regulation of Pride and Its Effects on Adaptability, Effort, and Organizational Citizenship Behaviors: The Case of Salespeople in the Netherlands and the Philippines. Unpublished working paper, Rice University.

Bagozzi, R.P., M. Bergami, and L. Leone. (2003) "Hierarchical Representation of Motives in Goal-setting." *Journal of Applied Psychology,* 88, 915–943.

Bagozzi, R.P., and J. Christian. (2005) Social Influence in Newly Formed Groups: The Roles of Attitudes, Compliance, Internalization, and Social Identity. Unpublished working paper, Rice University.

Bagozzi, R.P., and P.A. Dabholkar. (1994) "Consumer Recycling Goals and Their Effect on Decisions to Recycle: A Means-End Chain Analysis." *Psychology and Marketing,* 11, 313–340.

———. (2000) "Discursive Psychology: An Alternative Conceptual Foundation to Means-End Chain Theory." *Psychology and Marketing,* 17, 535–586.

Bagozzi, R.P., and U.M. Dholakia. (1999) "Goal-setting and Goal-striving in Consumer Behavior." *Journal of Marketing,* 63, 19–32.

———. (2002) "Intentional Social Action in Virtual Communities." *Journal of Interactive Marketing,* 16, 2–21.

———. (2005a) "Antecedents and Purchase Consequences of Customer Participation in Small Group Brand Communities." *International Journal of Research in Marketing,* forthcoming.

———. (2005b) Open Source Software User Communities: A Study of Participation in Linux User Groups. *Management Science,* forthcoming.

———. (2005c) "Three Roles of Past Experience in Goal Setting and Goal Striving." In *The Routines of Decision Making,* ed. T. Betsch and S. Haberstroh, pp. 21–38. Mahwah, NJ: Erlbaum.

Bagozzi, R.P., U.M. Dholakia, and S. Basuroy. (2003) "How Effortful Decisions Get Enacted: The Motivating Role of Decision Processes, Desires, and Anticipated Emotions." *Journal of Behavioral Decision Making,* 16, 273–295.

Bagozzi, R.P., U.M. Dholakia, and L.R. Klein Pearo. (2005) Antecedents and Consequences of Online Social Interactions. Unpublished working paper, Rice University.

Bagozzi, R.P., U.M. Dholakia, and A. Mookerjee. (2005) "Individual and Group Bases of Social Influence in Online Environments." *Media Psychology* (forthcoming).

Bagozzi, R.P., and E.A. Edwards. (1998) "Goal Setting and Goal Pursuit in the Regulation of Body Weight." *Psychology and Health,* 13, 593–621.

———. (2000) "Goal-striving and the Implementation of Goal Intentions in the Regulation of Body Weight." *Psychology and Health,* 15, 255–270.

Bagozzi, R.P., Z. Gürhan-Canli, and J.R. Priester. (2002) *The Social Psychology of Consumer Behavior.* Buckingham, UK: Open University Press.

Bagozzi, R.P., G. Henderson, P.A. Dabholkar, and D. Iacobucci. (1996) "Network Analyses of Hierarchical Cognitive Connections Between Concrete and Abstract Goals: An Application to Consumer Recycling Attitudes and Behaviors." In *Networks in Marketing,* ed. D. Iacobucci, pp. 367–383. Thousands Oaks, CA, Sage.

Bagozzi, R.P., and S.K. Kimmel. (1995) "A Comparison of Leading Theories for the Prediction of Goal-directed Behaviours." *British Journal of Social Psychology,* 34, 437–461.

Bagozzi, R.P., and K-H. Lee. (2002) "Multiple Routes for Social Influence: The Role of Compliance, Internalization, and Social Identity." *Social Psychology Quarterly,* 65, 226–247.

Bagozzi, R.P., K-H. Lee, and M.F. Van Loo. (2001) "Decisions to Donate Bone Marrow: The Role of Attitudes and Subjective Norms Across Cultures." *Psychology and Health,* 16, 29–56.
Bagozzi, R.P., D.J. Moore, and L. Leone. (2004) "Self-control and the Regulation of Dieting Decisions: The Role of Prefactual Attitudes, Subjective Norms, and Resistance to Temptation." *Basic and Applied Social Psychology,* 26, 199–213.
Bagozzi, R.P., W. Verbeke, and J.C. Gavino, Jr. (2003) "Culture Moderates the Self-Regulation of Shame and Its Effects on Performance: The Case of Salespersons in the Netherlands and the Philippines." *Journal of Applied Psychology,* 88, 219–233.
Bagozzi, R.P., and P.R. Warshaw. (1990) "Trying to Consume." *Journal of Consumer Research,* 17, 127–140.
Bagozzi, R.P., N. Wong, and Y. Yi. (1999) "The Role of Culture and Gender in the Relationship Between Positive and Negative Affect." *Cognition and Emotion,* 13, 641–672.
Bagozzi, R.P., and Y. Yi. (1989) "The Degree of Intention Formation as a Moderator of the Attitude-behavior Relation." *Social Psychology Quarterly,* 52, 913–929.
Bagozzi, R.P., Y. Yi, and J. Baumgartner. (1990) "The Level of Effort Required for Behavior as a Moderator of the Attitude-Behavior Relation." *European Journal of Social Psychology,* 20, 45–59.
Bargh, J.A. (1990) "Auto-motives: Preconscious Determinants of Social Interaction." In *Handbook of Motivation and Cognition,* vol. 2, ed. E.T. Higgins and R.M. Sorrentino, pp. 93–130. New York: Guilford Press.
———. (1997) "The Automaticity of Everyday Life." In *Handbook of Social Cognition,* vol. 10, ed. R.S. Wyer and T.K. Srull, pp. 1–61. Hillsdale, NJ: Erlbaum.
Bargh, J.A., and K. Barndollar. (1996) "Automaticity in Action: The Unconscious as Repository of Chronic Goals and Motives." In *The Psychology of Action: Linking Cognition and Motivation to Behavior,* ed. P.M. Gollwitzer and J.A. Bargh, pp. 457–481. New York: Guilford Press.
Bargh, J.A., M. Chen, M., and L. Burrow. (1996) "Automaticity of Social Behavior: Direct Effects of Trait Construct and Stereotype Activation on Action." *Journal of Personality and Social Psychology,* 71, 230–244.
Bargh, J.A., and M.J. Ferguson. (2000) "Beyond Behaviorism: On the Automaticity of Higher and Mental Processes." *Psychological Bulletin,* 126, 925–945.
Bargh, J.A., P.M. Gollwitzer, A. Lee-Chai, K. Barndollar, and R. Trötschel. (2001) "The Automated Will: Nonconscious Activation and Pursuit of Behavioral Goals." *Journal of Personality and Social Psychology,* 81, 1014–1027.
Baumeister, R.F. (1995) "The Need to Belong: Desire for Interpersonal Attachments as a Fundamental Human Motivation." *Psychological Bulletin,* 21, 1256–1268.
Baumeister, R.F., and K.D. Vohs. (eds.) (2004) *Handbook of Self-regulation: Research, Theory and Applications.* New York: Guilford Press.
Baumgartner, H., R. Pieters, and R.P. Bagozzi. (2004) Future-oriented Emotions: Conceptualization and Behavioral Effects. Unpublished working paper, Pennsylvania State University.
Bechara, A., H. Damasio, D. Tranel, and A. Damasio. (1997) "Deciding Advantageously Before Knowing the Advantageous Strategy." *Science,* 275, 1293–1295.
Belschak, F., W. Verbeke, and R.P. Bagozzi. (2005) "Coping with Social Anxiety by Salespersons: The Role of Situation Modification and Attention Deployment Strategies." Unpublished working paper, Rice University.
Benn, S. (1988) *A Theory of Freedom.* Cambridge: Cambridge University Press.
Bergami, M. and R.P. Bagozzi. (2000) "Self-categorization and Commitment as Distinct Aspects of Social Identity in the Organization: Conceptualization, Measurement, and Relation to Antecedents and Consequences." *British Journal of Social Psychology,* 39, 555–577.
Berofsky, B. (1987) *Freedom from Necessity.* London: Routledge and Kegan Paul.
Bettman, J.R. (1979) *An Information Processing Theory of Consumer Choice.* Reading, MA: Addison-Wesley.
Bishop, J. (1989) *Natural Agency: An Essay on the Causal Theory of Action.* Cambridge: Cambridge University Press.
Blackburn, S. (1994) *The Oxford Dictionary of Philosophy.* Oxford: Oxford University Press.
Bratman, M.E. (1987) *Intentions, Plans, and Practical Reason.* Cambridge, MA: Harvard University Press.
Brown, S., W. Cron, and J.W. Slocum. (1997) "Effects of Goal-directed Emotions on Salesperson Volitions, Behavior and Performance: A Longitudinal Study." *Journal of Marketing,* 61, 39–50.
Campbell, D.T. (1963) "Social Attitudes and Other Acquired Behavioural Dispositions." In *Psychology: A Study of a Science,* vol. 6, ed. S. Koch, pp. 94–172. New York: McGraw-Hill.

Carver, C.S., and M.F. Scheier. (1998) *On the Self-regulation of Behavior.* Cambridge: Cambridge University Press.

Chartrand, T.L., and J.A. Bargh. (1999) "The Chameleon Effect: The Perception-Behavior Link and Social Interaction." *Journal of Personality and Social Psychology,* 76, 893–910.

Chen, M., and J.A. Bargh. (1999) "Consequences of Automatic Evaluation: Immediate Behavioral Predispositions to Approach or Avoid the Stimulus." *Personality and Social Psychology Bulletin,* 25, 215–224.

*Concise Routledge Encyclopedia of Philosophy.* (2000) London: Routledge.

Cunningham, W.A., Preacher, K.J., and Banaji, M.R. (2001) "Implicit Attitude Measures: Consistency, Stability, and Convergent Validity." *Psychological Science,* 12, 163–170.

D'Andrade, R.G. (1992) "Schemas and Motivation." In *Human Motives and Cultural Models,* ed. R.G. D'Andrade and C. Strauss, pp. 23–44. Cambridge: Cambridge University Press.

Damasio, A.R. (1994) *Descartes' Error: Emotion, Reason, and the Human Brain.* New York: Avon Books.

———. (1999) *The Feeling of What Happens: Body and Emotion in the Making of Consciousness.* New York: Harcourt Brace.

Dasgupta, N., D.E. McGhee, A.G. Greenwald, and M.R. Banaji. (2000) "Automatic Preference for White Americans: Eliminating the Familiarity Explanation." *Journal of Experimental Social Psychology,* 36, 316–328.

Davidson, D. (1963) "Actions, Reasons, and Causes." Reprinted in D. Davidson, *Essays on Actions and Events.* Oxford: Oxford University Press.

Davis, W.A. (1997) "A Causal Theory of Intending." In *The Philosophy of Action,* ed. A.R. Mele, pp. 131–148. Oxford: Oxford University Press.

Dholakia, U.M., and R.P. Bagozzi. (2003) "As Time Goes By: How Goal and Implementation Intentions Influence Enactment of Short-Fuse Behavior." *Journal of Applied Social Psychology,* 33, 889–922.

Dholakia, U.M., R.P. Bagozzi, and L.R. Klein Pearo. (2004) "A Social Influence Model of Consumer Participation in Network- and Small-Group-Based Virtual Communities." *International Journal of Research in Marketing,* 21, 241–263.

Dholakia, U.M., M. Gopinath, and R.P. Bagozzi. (2005) The Role of Desires in Sequential Impulsive Choices. *Organizational Behavior and Human Decision Processes,* forthcoming.

Dijksterhuis, A., J.A. Bargh, and J. Miedema. (2000) "Of Men and Mackerels: Attention, Subjective Experience, and Automatic Social Behavior." In *The Message Within: The Role of Subjective Experience in Social Cognition and Behavior,* ed. H. Bess and J.P. Forgas, pp. 37–51. Philadelphia: Psychology Press.

Dijksterhuis, A., and A. van Knippenberg. (1998) "The Relation Between Perception and Behavior or How to Win a Game of Trivial Pursuit." *Journal of Personality and Social Psychology,* 74, 865–877.

Double, R. (1996) *Metaphilosophy and Free Will.* Oxford: Oxford University Press.

Dovidio, J.F., K. Kawakami, C. Johnson, B. Johnson, and A. Howard. (1997) "On the Nature of Prejudice: Automatic and Controlled Processes." *Journal of Experimental Social Psychology,* 33, 510–554.

Eagly, A.H., and S. Chaiken. (1993) *The Psychology of Attitudes.* Fort Worth, TX: Harcourt Brace Jovanovich.

Ekstrom, L.W. (2000) *Free Will: A Philosophical Study.* Boulder, CO: Westview Press.

Epictetus. (1995) *The Discourses of Epictetus.* London: J.M. Dent.

Fazio, R.H. (1990) "Multiple Processes by Which Attitudes Guide Behavior: The MODE Model as an Integrative Framework." In *Advances in Experimental Social Psychology,* vol. 23, ed. M.P. Zanna, pp. 75–109. New York: Academic Press.

———. (1995) "Attitudes as Object-Evaluation Associations: Determinants, Consequences, and Correlates of Attitude Accessibility." In *Attitude Strength: Antecedents and Consequences,* ed. R.E. Petty and J.A. Krosnik, pp. 247–282. Mahwah, NJ: Erlbaum.

Fazio, R.H., and B.C. Dunton. (1997) "Categorization by Race: The Impact of Automatic and Controlled Components of Racial Prejudice." *Journal of Experimental Social Psychology,* 33, 451–470.

Fazio, R.H., D.M. Sanbonmatsu, M.C. Powell, and F.R. Kardes. (1986) "On the Automatic Activation of Attitudes." *Journal of Personality and Social Psychology,* 50, 229–238.

Fazio, R.H., and C.J. Williams. (1986) "Attitude Accessibility as a Moderator of the Attitude-Perception and Attitude-Behavior Relations: An Investigation of the 1984 Presidential Election." *Journal of Personality and Social Psychology,* 51, 505–514.

Fischer, J.M. (1994) *The Metaphysics of Free Will: A Study of Control.* Oxford: Blackwell.

Fischer, K.W., and J.P. Tangney. (1995) "Self-conscious Emotions and the Affect Revolution: Framework and Overview." In *Self-conscious Emotions,* ed. J.P. Tangney and K.W. Fischer, pp. 3–24. New York: Guilford Press.

Fishbein, M. and I. Ajzen. (1975) *Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research.* Reading, MA: Addison-Wesley.
Forehand, M., and A. Perkins. (2005) "Implicit Assimilation and Explicit Contrast: The Unconscious Effects of Celebrity Voiceovers on Brand Attitude." *Journal of Consumer Research*, forthcoming.
Frankfurt, H. (1971) "Freedom of the Will and the Concept of a Person." *Journal of Philosophy,* 68, 5–20.
———. (1988) *The Importance of What We Care About.* New York: Cambridge University Press.
Frijda, N.H. (1986) *The Emotions.* Cambridge: Cambridge University Press.
———. (1993) "Moods, Emotion Episodes, and Emotions." In *Handbook of Emotions,* ed. M.L. Haviland and J.M. Haviland, pp. 381–403. New York: Guilford Press.
Gazzaninga, M.S. (ed.). (2004) *The Cognitive Neurosciences III.* Cambridge, MA: MIT Press.
Goddard, C. (1998) *Semantic Analysis: A Practical Introduction.* Oxford: Oxford University Press.
Godin, G., and G. Kok. (1996) "The Theory of Planned Behavior: A Review of Its Applications to Health-related Behaviors." *American Journal of Health Promotion,* 11, 87–98.
Goldman, A.I. (1970) *A Theory of Human Action.* Englewood Cliffs, NJ: Prentice-Hall.
———. (2000) "Folk Psychology and Mental Concepts." *ProtoSociology,* 14, 4–25.
Gollwitzer, P.M. (1990) "Action Phases and Mind Sets." In *Handbook of Motivation and Cognition,* vol. 2, ed. E.T. Higgins and R.M. Sorrentino, pp. 53–92. New York: Guilford Press.
———. (1993) "Goal Achievement: The Role of Intentions." *European Review of Social Psychology,* 4, 141–185.
———. (1996) "The Volitional Benefits of Planning." In *The Psychology of Action: Linking Cognition and Motivation to Behaviour,* ed. P.M. Gollwitzer and J.A. Bargh, pp. 287–312. New York: Guilford Press.
Gollwitzer, P.M., and V. Brandstätter (1997) "Implementation Intentions and Effective Goal Pursuit." *Journal of Personality and Social Psychology,* 73, 186–199.
Greenwald, A.G., and M.R. Banaji. (1995) "Implicit Social Cognition: Attitudes, Self-esteem, and Stereotypes." *Psychological Review,* 102, 4–27.
Greenwald, A.G., M.R. Banaji, L.A. Rudman, S.D. Farnham, B.A. Nosek, and D.S. Mellott. (2002) "A Unified Theory of Implicit Attitudes, Stereotypes, Self-esteem, and Self-concept." *Psychology Review,* 109, 3–25.
Greenwald, A.G., and S.D. Farnham. (2000) "Using the Implicit Association Test to Measure Self-esteem and Self-concept." *Journal of Personality and Social Psychology,* 79, 1022–1038.
Greenwald, A.G., D.E. McGhee, and J.K.L. Schwartz. (1998) "Measuring Individual Differences in Implicit Cognition: The Implicit Association Test." *Journal of Personality and Social Psychology,* 74, 1464–1480.
Harter, S. (1999) *The Construction of the Self.* New York: Guilford Press.
Heider, F. (1958) *The Psychology of Interpersonal Relations.* New York: John Wiley & Sons.
Heil, J. (1992) *The Nature of True Minds.* Cambridge: Cambridge University Press.
Higgins, E.T. (1997) "Beyond Pleasure and Pain." *American Psychologist,* 52, 1280–1300.
———. (1998) "Promotion and Prevention: Regulatory Focus as a Motivational Principle." In *Advances in Experimental Social Psychology,* vol. 30, ed. M.P. Zanna, pp. 1–46. New York: Academic Press.
Honderich, T. (ed.). (1995) *The Oxford Companion to Philosophy.* Oxford: Oxford University Press.
Hornsby, J. (1980) *Actions.* London: Routledge and Kegan Paul.
Hummel, J.E., and K.J. Holyoak. (2003) "A Symbolic-Connectionist Theory of Relational Inference and Generalization." *Psychological Review,* 110, 220–264.
Kandel, E., J. Schwartz, and T. Jessell. (2000) *Principles of Neural Science,* 4th ed. New York: McGraw-Hill.
Kane, R. (1996) *The Significance of Free Will.* Oxford: Oxford University Press.
Kim, J. (1990) "Supervenience as a Philosophical Concept." *Metaphilosophy,* 12, 1–27.
———. (2003) "Blocking Causal Drainage, and Other Maintenance Chores with Mental Causation." *Philosophy and Phenomenological Research,* 67, 151–176.
Kvavilashvili, L., and J. Ellis. (1996) "Varieties of Intention: Some Distinctions and Classifications." In *Prospective Memory: Theory and Applications,* ed. M. Brandimonte, G.O. Einstein,, and M.A. McDaniel, pp. 23–51. Mahwah, NJ: Lawrence Erlbaum.
Leone, L., M. Perugini, and R.P. Bagozzi. (2005) "Emotions and Decision Making: Regulatory Focus Moderates the Influence of Anticipated Emotions on Action Evaluations." *Cognition and Emotion,* forthcoming.
Lewin, K. (1951) *Field Theory in Social Science.* New York: Harper and Row.

Lewis, M. (2000) “Self-conscious Emotions: Embarrassment, Pride, Shame, and Guilt.” In *Handbook of Emotions,* 2d ed., ed. M. Lewis and J.M. Haviland Jones, pp. 623–636. New York: Guilford Press.

Mele, A.R. (1995) “Motivation: Essentially Motivation-Constituting Attitudes.” *Philosophical Review,* 104, 387–423.

Morandin, G., M. Bergami, and R.P. Bagozzi. (2005) “The Hierarchical Cognitive Structure of Entrepreneur Motivation Toward Private Equity Financing.” In *Starting Up and Growing New Adventures: The Role of the Financial Community,* ed. B. Clarysse, J. Roure, and T. Schamp, forthcoming. Cheltenham, UK: Edward Elgar.

Oatley, K., and P.N. Johnson-Laird. (1987) “Towards a Cognitive Theory of Emotions.” *Cognition and Emotion* 1, 29–50.

———. (1996) “The Communicative Theory of Emotions: Empirical Tests, Mental Models, and Implications for Social Interaction.” In *Striving and Feeling: Interactions Among Goals, Affect, and Self-regulation,* ed. L.L. Martin and A. Tesser, pp. 363–393. Mahwah, NJ: Erlbaum.

Ouellette, J.A., and W. Wood. (1998) “Habit and Intention in Everyday Life: The Multiple Processes by Which Past Behavior Predicts Future Behavior.” *Psychological Bulletin,* 124, 54–74.

Perugini, M., and R.P. Bagozzi. (2001) “The Role of Desires and Anticipated Emotions in Goal-directed Behaviors: Broadening and Deepening the Theory of Planned Behavior.” *British Journal of Social Psychology,* 40, 79–98.

———. (2004a) “An Alternative View of Pre-volitional Processes in Decision Making: Conceptual Issues and Empirical Evidence.” In *Contemporary Perspectives on the Psychology of Attitudes,* ed. G. Haddock and G.R. Maio, pp. 169–201. Hove, UK: Psychology Press.

———. (2004b) “The Distinction Between Desires and Intentions.” *European Journal of Social Psychology,* 34, 69–84.

Perugini, M., and M. Conner. (2000) “Predicting and Understanding Behavioral Volitions: The Interplay Between Goals and Behaviors.” *European Journal of Social Psychology,* 30, 705–731.

Pieters R., H. Baumgartner, and D. Allen. (1995) “A Means-End Chain Conceptualization of Consumers’ Goal Structures.” *International Journal of Research in Marketing,* 12, 227–244.

Pietroski, P.M. (2000) *Causing Actions.* Oxford: Oxford University Press.

Posavac, S.S., D.M. Sanbonmatsu, and R.H. Fazio. (1997) “Considering the Best Choice: Effects of the Salience and Accessibility of Alternatives on Attitude-Decision Consistency.” *Journal of Personality and Social Psychology,* 34, 9–21.

Rosenthal, R., and D.B. Rubin. (1982) “Comparing Effect Sizes of Independent Studies.” *Psychological Bulletin,* 92, 500–504.

Rozin, P. (2001) “Social Psychology and Science: Some Lessons from Solomon Asch.” *Personality and Social Psychology Review,* 5, 2–14.

Ryle, G. (1949) *The Concept of Mind.* New York: Barnes and Noble.

Shadish, W.R., T.D. Cook, and D.T. Campbell. (2001) *Experimental and Quasi-experimental Designs for Generalized Causal Influences.* Boston: Houghton-Mifflin.

Sheeran, P. (2002) “Intention-Behaviour Relations: A Conceptual and Empirical Review.” In *European Review of Social Psychology,* vol. 12, ed. M. Hewstone and W. Stroebe, pp. 1–36. Chichester, UK: Wiley.

Smilansky, S. (2000) *Free Will and Illusion.* Oxford: Clarendon Press.

Smith, E.R., and J. DeCoster. (2000) “Dual Process Models in Social and Cognitive Psychology: Conceptual Integration and Links to Underlying Memory Systems.” *Personality and Social Psychology Review,* 4, 108–131.

Stein, N.L., T. Trabasso, and M.D. Liwag. (2000) “A Goal Appraisal Theory of Emotional Understanding: Implications for Development and Learning.” In *Handbook of Emotions,* 2d ed., ed. M. Lewis and J.M. Haviland, pp. 436–457. New York: Guilford Press.

Strack, F., and R. Deutsch. (2004) “Reflective and Impulsive Determinants of Social Behavior.” *Personality and Social Review,* 8, 220–248.

Swanton, C. (1992) *Freedom: A Coherence Theory.* Indianapolis, IN: Hackett.

Taylor, S.D., Bagozzi, and C.A. Gaither. (2001) “Gender Differences in the Self-regulation of Hypertension.” *Journal of Behavioral Medicine,* 24, 469–487.

Taylor, S.D., R.P. Bagozzi, C.A. Gaither, and K.A. Jamerson. (2005a) “Goal Setting and Self-regulation by Hypertensive Patients.” *Journal of Health Psychology,* forthcoming.

———. (2005b) “Decision Making and Effort in the Self-regulation of Hypertension: Testing Two Competing Theories.” *British Journal of Health Psychology,* forthcoming.

Triandis, H.C. (1977) *Interpersonal Behavior.* Monterey, CA: Brooks/Cole.
Vera, A.H., and H.A. Simon. (1993) "Situated Action: A Symbolic Interpretation." *Cognitive Science,* 17, 7–48.
Verbeke, W., and R.P. Bagozzi. (2000) "Sales Call Anxiety: Exploring What It Means When Fear Rules a Sales Encounter." *Journal of Marketing,* 64, 88–101.
———. (2002) "A Situational Analysis on How Salespeople Experience and Cope with Shame and Embarrassment." *Psychology and Marketing,* 19, 713–741.
———. (2003) "Exploring the Role of Self- and Customer-Provoked Embarrassment in Personal Selling." *International Journal of Research in Marketing,* 20, 233–258.
Verbeke, W., F. Belschak, and R.P. Bagozzi. (2004) "The Adaptive Consequences of Pride in Personal Selling." *Journal of the Academy of Marketing Science,* 32, 386–402.
Verplanken, B., and H. Aarts. (1999) "Habit, Attitude, and Planned Behavior: Is Habit an Empty Construct or an Interesting Case of Goal-directed Automaticity?" In *European Review of Social Psychology,* 10, ed. W. Stroebe and M. Hewston, pp. 101–134. Chichester, UK: John Wiley & Sons.
Vohs, K.D., and R.F. Baumeister. (2004) "Understanding Self-regulation: An Introduction." In *Handbook of Self-Regulation: Research, Theory, and Applications,* ed. R.F. Baumeister and K.D. Vohs, pp. 1–9. New York: Guilford Press.
Warshaw, P.R. and F.D. Davis. (1985) "Disentangling Behavioral Intention and Behavioral Expectation." *Journal of Experimental Social Psychology,* 21, 213–228.
Wierzbicka, A. (1996) *Semantics: Primes and Universals.* Oxford: Oxford University Press.
Williams, C. (1980) *Free Will and Determinism.* Indianapolis, IN: Hackett.
Wilson, T.D., S. Lindsey, and T.Y. Schooler. (2000) "A Model of Dual Attitudes." *Psychological Review,* 107, 101–126.
Wittgenstein, L. (1997) *Philosophical Investigations,* reissued 2d ed. Trans. G.E.M. Anscombe. Oxford: Blackwell.

CHAPTER 2

# LOOKING THROUGH THE CRYSTAL BALL

## Affective Forecasting and Misforecasting in Consumer Behavior

DEBORAH J. MACINNIS, VANESSA M. PATRICK, AND C. WHAN PARK

**Abstract**

*A recent addition to the literature in psychology concerns individuals' forecasts of the affective states they predict will arise in the future. Affective forecasts are extremely relevant to marketing and consumer behavior as they impact choice as well as a set of other marketing-relevant outcomes. Interestingly, however, affective forecasts are often erroneous because they are susceptible to a variety of errors and biases that reduce their accuracy. As a result, experienced affect differs from forecasted affect, and affective misforecasting (hereafter AMF), occurs. This chapter reviews the literature on affective forecasting, indicates the importance and relevance of this area of research to consumer behavior and marketing, and identifies the factors that lead to errors in affective forecasting and hence result in affective misforecasting. Our review is designed to both illustrate the relevance of affective forecasting and misforecasting to marketing and consumer behavior and to identify novel research directions for future work in this research domain.*

Considerable research in consumer behavior has examined consumers' affective experiences (Holbrook and Batra, 1987; Edell and Burke, 1987; Bagozzi and Moore, 1994) and how they influence information processing (Isen, 1999), product evaluation (Howard and Gengler, 2001; Meloy, 2000), and choice (Pham, 1998; Bagozzi et a1., 2000; Luce et a1., 1999). Notably, however, consumer researchers have focused on feelings experienced *at the time of processing or choice* as opposed to feelings *anticipated to occur in the future.* The omission of anticipated affect in the consumer behavior literature is significant, especially since research elsewhere alludes to its potential relevance to our field. This chapter focuses on issues concerning the role of consumers' processing of affect anticipated to occur in the future.

All normally functioning human beings have a "model of the future" that forms the basis for goal setting, planning, exploring options, making commitments, and having hopes, fears and desires (Trommsdorff, 1983; Markus and Nurius, 1986; Nurmi, 1991; Snyder, 2000; Bandura, 2001). One way in which people think about the future is to attempt to *predict* what the future has in store (Johnson and Sherman, 1990). Research dealing with prediction of the future has been examined in the context of decision making under uncertainty (Nisbett and Ross, 1980; Kahneman and Tversky, 2000), the predictions of future activities, events, and behaviors (Carroll, 1978; Sherman, Zehmer et al., 1983; Vallone, Griffin et al., 1990; Buehler, Griffin et al., 1994), the prediction of future self-concepts (Markus and Nurius, 1986; Markus and Ruvolo, 1989), the effects of temporal perspectives on prediction (Liberman and Trope, 1998; Trope and Liberman, 2000), and the role of imagery (Anderson, 1983), positive illusions (Taylor and Brown, 1988), and optimistic biases in prediction (Weinstein, 1980; Armor and Taylor, 1998).

A recent addition to the literature in psychology represents the intersection of work on affect and prediction and concerns a phenomenon called *affective forecasting* (Gilbert et al., 1998). Interestingly, although research suggests that affective forecasting occurs in a wide variety of circumstances, it also indicates that these forecasts are often erroneous as they are susceptible to a variety of biases that reduce their accuracy (Kahneman and Snell, 1992; Loewenstein and Adler, 1995; Snell, Gibbs, and Varey, 1995; Loewenstein and Frederick, 1997; Mitchell, Thompson et al., 1997; Gilbert, Pinel et al., 1998; Read and Leeuwen, 1998; Frederick and Loewenstein, 1999; Gilbert, Brown et al., 2000; Loewenstein, O'Donoghue et al., 2000; Loewenstein and Schkade, 2000; Wilson, Wheatley et al., 2000). Specifically, experienced affect differs from forecasted affect, and *affective misforecasting* (hereafter AMF) occurs.

In this chapter, we review the literature on affective forecasting and misforecasting. We indicate the importance and relevance of these two research domains to consumer behavior and marketing and identify novel research directions for future work in these areas.

## Affective Forecasting

Since the term "affective forecasting" may be new to some readers, below we present an overview of the concept, including a definition, clarification of terms, and a discussion of the dimensions along with affective forecasting can be described.

### *What Is Affective Forecasting?*

#### *Definition*

Affective forecasting, defined as the prediction of one's own future feelings, reflects the intersection of research on prediction, affect, and the self. Although it falls within the domain of prediction of the future, it is differentiated from research on prediction of self-related *behavioral* outcomes such as the predictions of usage (Folkes et al., 1993; Nunes, 2000), or the prediction of future behavior/intentions (Sherman, 1980; Morwitz and Fitzsimons, 2004) by its focus on self-relevant affective outcomes. By its focus on affect, it also differs from the prediction of *cognitive* outcomes such as expectations regarding future outcomes (Cadotte et a1., 1987, Stayman et a1., 1992).

#### *The Meaning of Affect*

The term *affect* is used broadly in this literature to include a variety of affective experiences including *visceral (or bodily) feelings* (such as thirst, sexual drive, pain, and hunger; Loewenstein, Nagin, and Paternoster, 1997; Loewenstein, 1996),[1] *preferences or tastes* (Loewenstein and Adler, 1995), *generalized valenced feeling states* (e.g., feeling good or bad), and *specific emotional states* (Simonson, 1992; Bagozzi, Baumgartner et al., 1998; Shiv and Huber, 2000; Perugini and Bagozzi, 2001; Raghunathan and Irwin, 2001; Crawford, McConnell et al., 2002).

To further illustrate the meaning of affect, consider, for example, the view of Mellers and

McGraw (2001) who identify specific emotions forecasted in a choice task, the occurrence of which depends on whether the frame of reference is on the chosen or nonchosen option and whether the outcome of that option is good or bad. *Elation* or *happiness* is predicted when a good outcome is associated with the chosen option. *Disappointment* is forecasted when a bad outcome is associated with that same chosen option. Individuals forecast *regret* when a good outcome accrues to an option not chosen, and they forecast *rejoicing* when a bad outcome is predicted to accrue to a nonchosen option (see also Zeelenberg et al., 1996). Other emotions are also relevant and include affective states already examined in the literature such as anticipated *satisfaction* (Shiv and Huber, 2000), and *guilt and shame* (Patrick, MacInnis, and Matta, 2004), as well as other emotions (e.g., disgust, relaxation, rage, ecstasy) that have not yet been the topic of empirical study.

#### *The Dimensions of Affective Forecasting*

Forecasts of affective experiences can be described in terms of several dimensions that reflect (a) what will I feel, (b) how much, and (c) for how long (see the lower right-hand box in Figure 2.1). The dimension of valence deals with the specific feeling forecasted (will I feel good or bad? happy or sad?). The dimension of *intensity* deals with the strength of the feeling (e.g., will I feel a bit relaxed or totally relaxed?). Finally, the dimension of *duration* deals with the length of the affective experience (will I feel happy for just an hour or for a week?).

### ***The Relevance of Affective Forecasting: Why Should We Care?***

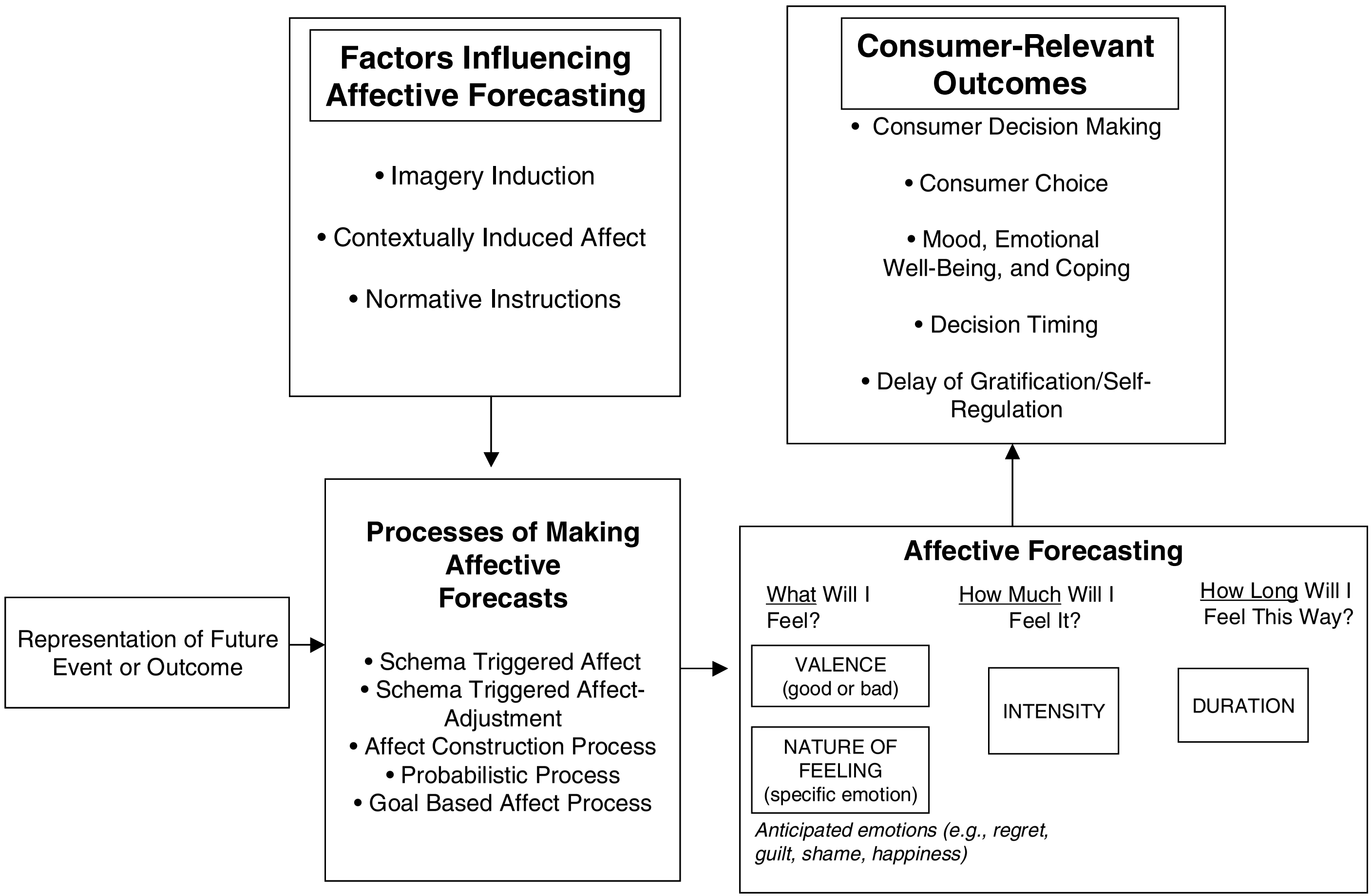
Affective forecasting is relevant to several domains of consumer behavior and marketing. Following Figure 2.1, we consider its relevance to several (nonexhaustive) domains, including (a) consumer decision making, (b) consumer choice, (c) mood, emotional well-being, and coping, (d) decision timing, and (e) delay of gratification and self-regulation.

#### *Relevance to Decision-Making Theory*

From a theoretical perspective, ideas regarding affective forecasting offer some fundamentally different views on decision theory based on the notion of utility. Mellers (2000) argues that in its original conception, Bernoulli defined "utility" as an affective forecast—that is, "the anticipated pleasure or psychological satisfaction of wealth rather than wealth per se" (p. 910) and that this expected (or forecasted) utility (pleasure/satisfaction) drives decision making. However, in the early nineteenth and twentieth centuries, the notion of utility as anticipated affect was replaced by indifference curves that used interval meaning based on ranked-ordered preferences, not unobservable psychological experiences. This transformation, though allowing for the development of axioms and mathematically testable principles, removed affective forecasting from the realm of classical decision making.

As research on classical decision-making theory advanced, deviations from the classic utility-maximizing model were observed, leading to observations about risk propensities in the gain and loss domain as specified by Prospect Theory (Kahneman and Tversky, 1979). Lopes (1984, 1987, 1990) further modified classical decision theory by suggesting that anticipatory feelings such as hope, fear, optimism, pessimism, and related feelings about risk and uncertainty explain decision outcomes. Recent work has taken into account anticipated emotions, such as affective forecasts of regret, rejoicing, and satisfaction (Bell, 1982; Loomes and Sunden, 1982; Ritov and Baron,

Figure 2.1 **Affective Forecasting and Its Relevance to Consumer Behavior and Marketing**



1990). The incorporation of these forecasted affective experiences into decision theory seems to bring us full circle to the original meaning of utility as defined by Bernoulli.

*Relevance to Consumer Choice*

As suggested by Figure 2.1, affective forecasting is also relevant to marketing and consumer behavior given its direct implications for consumer choice. Prior research suggests that choice may be *predicated on* the affect we anticipate will arise from choice. As such, *affective forecasts may be a central driver of choice outcomes.* For example, the consumption of symbolic products is predicated on feelings of anticipated security, comfort, belonging, and pride. We purchase functional products such as dishwashers or sprinkler systems on the basis of the feelings of relief we will have at having some one or some thing do chores that would otherwise fall on our shoulders. Consumption of self-help books and psychological therapy are anticipated to reduce feelings of helplessness, guilt, anger, depression, and anxiety. Medication is anticipated to result in the reduction of pain. Experiential products and services (spas, river rafting, movies, vacations, art, and pets) are consumed for the anticipated joy, relaxation, excitement, and pleasure they will evoke.

Several studies empirically demonstrate the influence of affective forecasts on choice. Zeelenberg et al. (1996) examine the extent to which predictions of *regret* influenced decision making. They convincingly argue that prior research which suggests that consumers avoid risk in decision making has confounded risk with forecasted affect of regret. In a series of studies, they independently manipulate risk and feedback designed to evoke the potential for regret. Their results show that in contrast to previous studies, there are certain circumstances in which people seek (not avoid) risk, and that *what consistently affects choice is not perceptions of risk per se but consumers' desire to avoid regret.*

Simonson (1992) also showed that anticipated *regret* influences decision making. He demonstrates that anticipating the regret associated with the choice of two items can affect which option is chosen as well as the timing of the decision. With regard to the latter, consumers were more likely to prefer to buy an item on sale today if asked to anticipate the regret they would feel if they waited for better sales in the future but later discovered that the present sale was better. With regard to the former, consumers asked to anticipate the regret associated with a purchase were more likely to choose a better known, though more expensive, brand than a lesser known and less expensive brand.

The anticipation of other emotions has also been linked to choice. For example, Mellers and McGraw (2001) showed that anticipated *pleasure* predicts choice and that it improves the prediction of choice beyond that explained by utilities alone.

Richard, van der Plight, and de Vries (1996) found that affective forecasts add to the predictive power of attitudes and other factors in the prediction of behavioral intentions—an antecedent to choice. To demonstrate this effect, they selected consumption contexts where consumers were expected to like a product (e.g., junk food, alcohol, marijuana) but anticipate *feeling bad* after its consumption. They found that behavioral intentions regarding the consumption of these products were significantly impacted by the anticipated negative feelings following their consumption, over and above the effects of attitudes, perceived behavioral control, and subjective norms.

*Relevance to Mood, Emotional Well-Being, and Coping*

As Figure 2.1 suggests, another way in which affective forecasting is relevant to consumer behavior is with regard to mood-induction and consumer well-being. Human beings have a fundamental motivation to seek pleasure and avoid pain. Moreover, the *anticipation of future feelings can evoke* *pleasure and pain in the present.* Indeed, as Loewenstein (1987) quotes from Bentham (1789/1948), "anticipation, like consumption itself, is an important source of pleasure and pain" (p. 666).

Anticipating pleasure may thus have positive mood-altering properties, making one feel good at the moment. Analogously, anticipating pain may induce depressive affect. As evidence, Andersen and Lyon (1987) found that anticipating negative outcomes that were also viewed as inevitable induced depression, anxiety, and hostility in the present. Given the voluminous research on the impact of mood on product evaluation and choice, it is interesting to consider whether affective forecasts of different valence, intensity, or duration may lead to different choices or outcomes owing to their mood-altering properties. Interestingly, research has not examined the extent to which the impact of mood on evaluations and choices is induced by affective forecasts or whether and how mood based on affective forecasts influences product evaluation and choice.

Given its potential mood-altering effects, *the forecasting of positive future affect may also facilitate coping with negative current states* (see Figure 2.1). Indeed, research in medicine shows that individuals who forecast the reduction of negative emotions and the possible occurrence of positive ones show greater pain endurance, more proactive and more positive self-care practices, delayed illness timing, less severe illnesses, and illnesses of shorter duration (see Snyder, 2000; Taylor et a1., 2000; Groopman, 2004). Affective forecasting of positive emotions may also help consumers cope with more mundane problems. Since consumer products are often touted as solutions to health, beauty, and relationship problems, consumer goods may be viewed as sources of positive future feelings that facilitate coping with failing health, beauty, and relationships or even with negative feelings caused by the discrepancy between actual and normatively appropriate behavior. In line with this notion, Raghunathan and Trope (2002) examined the effects of current positive versus negative mood on the willingness and ability to cope with negative but relevant information (e.g., information about the effects of caffeine consumption on one's health for a heavy drinker of coffee). They found that positive mood provides a "buffer" or a "resource" (what they termed the mood-as-a-resource hypothesis) that helps consumers cope with negative (but self-relevant) information. Although research has not substantiated a link between affective forecasting and coping in a *consumer domain,* the research above suggests its potential impact.

*Relevance to Decision Timing*

Another potential outcome relevant to affective forecasting and consumer behavior concerns the impact of the valence of affective forecasting on decision timing. Loewenstein (1987) argues that we sometimes delay consumption (e.g., deferring a vacation, storing a bottle of fine wine for a special occasion) so as to *savor* the possibility of a good future experience. Relatedly, Chew and Ho (1994) suggest that consumers may delay scratching numbers off a lottery ticket to savor the good feelings that accompany the possibility of a win. Anticipation of future positive affect may well delay consumption of objects assumed to elicit positive affect so as to invoke a state of savoring. On the other hand, anticipation of negative future affect may either hasten choice and consumption so that negative anticipated emotions can be quickly gotten over with (e.g., gulping bad-tasting medicine) or lead to procrastination and delay to avoid the negative affect (e.g., putting off balancing one's check book).

*Relevance to Delay of Gratification/Self-Regulation*

A related issue concerns the role of affective forecasting in delay of gratification as it pertains to consumer self-regulation. Many consumers are beset by problems of self-regulation as evidenced by overeating, compulsive shopping, gambling, drug use, smoking, and alcoholism. In many cases, problems exist despite consumers' rational knowledge that their consumption means foregoing a larger and more important long-term goal. Hoch and Lowenstein (1991) call these "time-inconsistent preferences" since the immediate behavior consumers want to engage in is inconsistent with the longer-term goal they would like to achieve. Time-inconsistent preferences occur when the *desire* for a given behavior (e.g., eating, drinking, smoking) is greater than the *willpower* the consumer has to forego this behavior in light of a larger goal (e.g., weight loss, sobriety, nicotine free living). Recent research has verified that desire and willpower are indeed related to time-inconsistent preferences, at least in the domain of economic spending (Karlsson, 2003).

Time-inconsistent preferences create a conflict between near-term and far-term forecasted affect. Anticipated bliss at delving into a piece of chocolate cake may be forecasted in the near term, with guilt, regret, and anger at oneself forecasted in the longer term. Denial of the near-term goal produces a forecast of negative emotions, with positive emotions from the denial anticipated in the far term. As it pertains to consumer self-regulation, interesting opportunities exist for research which examines factors that enhance self-regulatory capacities by reducing the anticipated positive emotions associated with the near-term goal and enhancing the positive emotions associated with the long-term goal.

Research in psychology on delay of gratification (e.g., Metcalfe and Mischel, 1999) suggests that when near-term positive forecasted emotions are activated (or are "hot") delay of gratification is quite difficult. Metcalfe and Mischel (1999) suggest that, in order to reduce activation of these "hot" nodes, the stimulus evoking the "hot" affect must be either externally obscured or involve an internal reallocation of attention to the stimulus. Note that the very act of affective forecasting involves attention to the emotion presumed to arise from the stimulus or outcome. While reallocation strategies may involve elements of the "cool" system that are unrelated to the hot system, another strategy is to shift attention to a different element in the hot system. Here *delay of gratification may be achieved by focusing attention on the anticipated positive emotions associated with the achievement of the far-term goal* (e.g., pride from being able to stay away from the chocolate cake).

A second strategy noted for delaying gratification is to *reconstrue the meaning of the near-term hot stimulus so as to make it affectively negative as opposed to positive.* Within an affective forecasting paradigm, one way of reconstruing the meaning of the stimulus (e.g., chocolate cake is good because it tastes great) is to link it to the negative far-term emotion anticipated to arise from its consumption (chocolate cake is bad because it will make me feel guilty). Although prior research has not examined affective forecasting as it applies to the delay of gratification and self-regulation, we believe there are opportunities for extensions in this area.

### *Processes of Making Affective Forecasts*

Although research on the process by which affective forecasts are made is still in its infancy, we develop below a conceptualization of potential processes, several of which have received support from the literature. These processes vary in terms of the nature and extent of *elaboration* (e.g., automatic vs. constructed through deliberate processing), and are illustrated in Figure 2.1.

One process by which affective forecasts may arise is through *schema-triggered affect* (Fiske and Pavelchak, 1986). When the memory of an object or outcome (e.g., a vacation) is well-entrenched and organized in a schema, the affect attached to the schema is automatically retrieved when the schema is activated. This affect is not derived by a conscious process but is generated automatically from accessed memory. Consumption experiences or outcomes that are well entrenched in memory (e.g., some experiential products and services like vacations, pets, or dentist appointments) tend to automatically elicit affect as soon as they are accessed in memory, particularly if the affect attached to these schemas is extreme. With schema-triggered affect, the automatic activation of affect as a by-product of a well-developed schema may be used as a basis for predicting one's affective reaction to a similar (schema-consistent) outcome.

The *schema-triggered affect adjustment process,* also called a *heuristic-based process* (Snell and Gibbs, 1995), presumes greater elaboration than the schema-triggered affect process just described. The primary distinction is that affect automatically activated from a schema is adjusted and edited through cognitive elaboration for its intensity and/or its valence. For example, Snell and Gibbs (1995) propose that, when predicting how much they will like something in the future, consumers should use their current liking for the entity and then adjust it based on lay theories about the impact of time, experiences, or the situation in which it is to be evaluated.

The *affect construction process* suggests that forecasted affect is constructed from elaboration of the consumption of the product or service. For example, Phillips, Olson, and Baumgartner (1995; Phillips 1996) propose that consumers develop "consumption visions" or mental images of themselves interacting with a product and imagine the various outcomes arising from this interaction. Patrick and MacInnis (2002) document this imagery process associated with affective forecasting of future feelings associated Spring Break. Gilbert et al. (2002) offer a view that augments the imagery process just described with adjustments for time and context. They suggest that individuals first imagine the event to be experienced in the future, though they typically do not incorporate into their imagery the temporal context in which they future event will happen. Individuals then develop "proxy reactions," to that event, which are in turn adjusted for how their feelings might change if the event were displaced in time.

At even greater levels of elaboration, consumers may even consider the probability of a given outcome; the affect predicted to arise in the future depends on the perceived probability that a given event will occur. For example, the forecast of satisfaction is based on an assessment of the perceived probability by which consumption of a given product or service (e.g., floor wax) will lead to an outcome desired by consumers (e.g., shiny floors). Mellers and McGraw's (2001) decision affect theory is reflective of this *probabilistic process.* These authors suggest that consumers first predict the pleasure and pain of future outcomes, weigh these feelings by the probability that they will occur, and then choose the option that is likely to give them the greatest pleasure. The notion of anticipated pleasure weighted by an outcome's probability might be called optimism or hopefulness. Decision affect theory might be conceptualized within the context of a multi-attribute attitude model, where the attributes are the anticipated feelings and the belief strengths are the probabilities that they will occur.

*A goal-based affect* process suggests that consumers first specify an affective goal—specifically, an emotional state that they *wish to feel* in the future (e.g., relaxation) and then mentally construct images of which consumption options will best deliver that affective state (e.g., a vacation to Hawaii? to the mountains? to Europe?) Here, anticipated affect reflects an ultimate goal in a means–end chain. Indeed, well-being or happiness may well be regarded as ultimate affective states that drive all of human behavior (Lyubomirsky and Tucker, 1998; Lyubomirsky 2001). Many experiential consumption experiences such as going to the movies, attending sports games, book readings, etc. are driven by affective goals regarding specific emotions we would like to experience. This process resembles the above affect construction process described above as it involves considerable elaboration. However, here consumers first ask themselves, "how do I want to I feel?" and then compare the forecasted and desired affective experience so as to determine whether or not to engage in consumption (should I watch this movie or not?), or choose between competing options (should I watch this movie or that one?).

As Figure 2.1 suggests, each of the above process models shares in common the idea that affective forecasts are predicated on a representation of a future event and an invocation of the affective reactions to this event. Notably, these models of the process of affective forecasting are tentative, and research has not established the nature of the process or the extent to which the process varies as a function of a set of moderating variables. Hence considerable opportunity exists for developing and validating process models of affective forecasting.

### *Inducing Affective Forecasting*

Given the potential relevance of affective forecasting to consumers and marketers as described above, a critical question concerns how marketers can stimulate (and influence) affective forecasting. Although little research has been done on this topic, thoughts about potential research directions are described below and depicted in Figure 2.1.

#### *Imagery Induction*

Since affective forecasting involves a mental representation of an event and potentially an imagined response to that event (see Figure 2.1), factors that influence the representation and imagery of the event and one's emotional reaction to it may also induce affective forecasting. Prior research on imagery shows that factors that induce imagery include the presentation of case versus base rate information, imagery instructions, and concrete words (MacInnis and Price, 1987; Park and Young, 1986; Pham, Meyvis, and Zhou, 2001). Although research has examined these factors as predictors of imagery, their use as predictors of the affect forecasted to arise from these imagined experiences has not yet been examined. The exception is Phillips (1996), though even her study relates only indirectly to affective forecasting. She reported that consumers had more detailed consumption images, more favorable ad attitudes, more positive attitudes toward acting, and more favorable behavioral intentions regarding a vacation to Aruba when exposed to an ad that had more rather than less visual detail about the experience of being in Aruba. Instructions to imagine had no effect on these outcomes, and the provision of verbal detail had mixed effects on the results. Advertising is potentially an effective way to induce imagery for future consumption, which may in turn result in affective forecasts.

In addition to externally stimulated imagery, affective forecasts may be impacted by individual differences in capacities to generate images. MacInnis (1987) reviews research on and scales developed to assess a number of different individual difference variables in imagery processing. Among these variables are (a) imagery vividness, which refers to the ability with which one can evoke clear images, (b) imagery control (i.e., the extent to which one can manipulate, transform, and hold images in mind at will), (c) involvement in fantasy, and (d) propensities toward daydreaming. Any one of these individual difference factors may impact the nature and extent of affective forecasting.

Interestingly, individual differences may alter the impact of externally stimulated imagery on affective forecasting. Pham, Meyvis, and Zhou (2001) found that consumers who were described as high on chronic imagery vividness capacity were less responsive to vivid and salient information in advertising as their internally generated images seemed to create an immersion in the imagery experience which overrode the use of imagery-evocative external cues. Although this study did not deal with affective forecasting, the results do suggest that the impact of externally provided imagery inducements on the nature or intensity of affective forecasts may be moderated by individual differences in imagery vividness.

*Contextually Induced Affect*

Feelings experienced at the time of the forecast may also influence affective forecasting. Patrick et al. (2004) demonstrated that ambient mood influenced consumers' forecasted affective states for neutral but not positive or negatively valenced future experiences.[2] Furthermore, Raghunathan and Corfman (2004) found that experienced anxiety and sadness impact the way consumers think about future events. These authors found that sadness leads to seeking pleasurable stimuli and preferring to complete a pleasurable activity before an important/urgent one, whereas anxiety leads to increased attentiveness and a preference for completing a more important activity before a pleasurable one.

*Normative Instructions*

Finally, Baron (1992) shows that normative instructions about how one *should* feel influence affective forecasts and the choices that result from them. Advertisements that present normative arguments about how one should feel (e.g., you should feel good about campaigning against tobacco advertising because each year 20,000 people die from smoking-related diseases) may heighten the intensity of the feelings consumers anticipate from future choices (e.g., decisions to join an antitobacco crusade).

Whereas the previous sections suggest that affective forecasting may be quite relevant to marketing and consumer behavior, a question of equal import concerns the *accuracy* of these forecasts. As described below, considerable research in psychology suggests that affective forecasts are rarely accurate. Next we explore research on why this is so and what implications it has for consumer-related outcomes such as satisfaction and repeat purchase behavior.

## Affective Misforecasting

Affective misforecasting refers to the difference (or gap) between forecasted and actual (experienced) affect. Because there is uncertainty regarding how one will feel in the future, it is natural that the affect we experience from consumption may not mirror the affect we had anticipated we would feel. Indeed, Loewenstein and Schkade (2000) note that the misforecasting of future tastes or feelings is measured in any number of units—the misforecasting of marital bliss—divorce; the misforecasting of long-term career preferences—burnout; and the misprediction of consumer purchases—dissatisfaction.

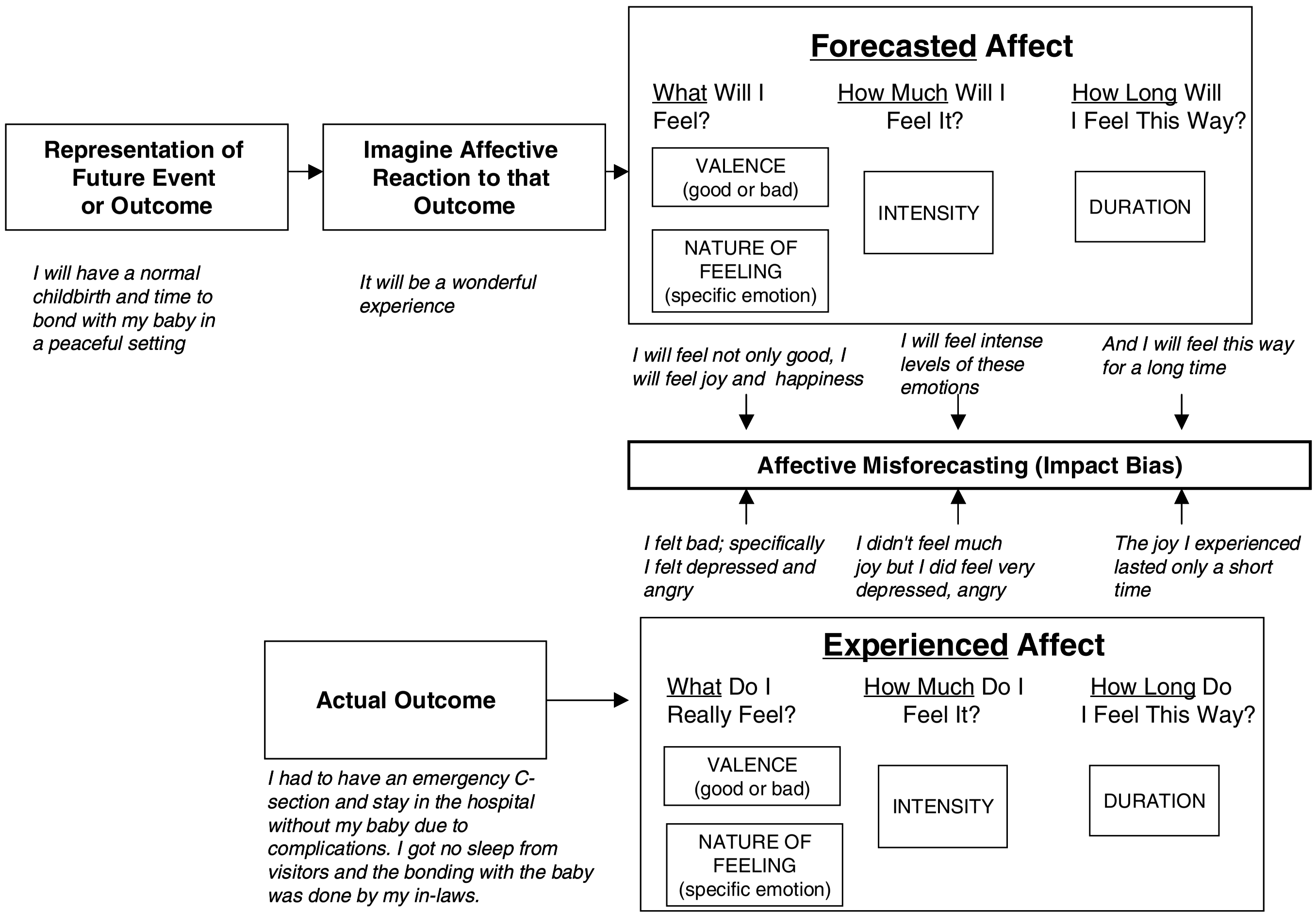
Indeed, research has long examined the psychological issues associated with a time perspective. A variety of studies conducted in psychology, the behavioral sciences, and political science point to one consistent theme, namely, that the value of outcomes change over time (e.g., Loewenstein and Prelec, 1993; Metcalfe and Mischel, 1999; Trope and Liberman, 2003). The study of affective misforecasting contributes to this literature by examining how actual feelings (outcomes) differ from predicted feelings as a result of the temporal distance between the time of prediction and the time of experience.

Before moving to consideration of the importance of affective misforecasting and why it occurs, we wish to note that, like affective forecasting, affective misforecasting can be described in terms of a set of dimensions.

### *Dimensions of Affective Misforecasting*

Since consumers can make forecasts of valence or specific emotions, the intensity, and the duration of a projected affective response, affective misforecasting can occur along any of these dimensions, as shown in Figure 2.2.

Figure 2.2 **Affective Forecasting and Affective Misforecasting: An Illustrative Example**



### *Valence and Specific Emotions*

First, consumers can misforecast the general affective *valence or the specific feelings* that will arise in the future. As shown in Figure 2.2, for example, our consumer predicted that she would feel good (specifically, feel joy and happiness) after the birth of her child. In contrast, she actually felt bad (angry and depressed).

Prior research suggests that in many circumstances people are relatively accurate at predicting the *general valence* of their future affective states (Baron, 1992). Consumers are typically able to predict that receiving a surprise gift is likely to make them feel positive, not negative, while a visit to the dentist will make them feel negative, not positive.

Consumers' accuracy in predicting *specific emotional* states has, however, revealed mixed results. Some research finds that consumers' affective forecasts of specific emotions are quite accurate; whereas others find that they are not.

Robinson and Clore (2001) found evidence that consumers *were accurate* in the prediction of specific emotions. They asked people to read descriptions of emotion-generating pictures (smiling babies, war scenes) and asked them to predict how the actual pictures would make them feel. These predictions were compared with the reports of people who actually viewed the pictures. The predictions and actual emotional experiences converged. In addition, a cluster analysis of the predicted and actual emotions also revealed similar structures. Note however, that here the accuracy of affecting forecasting was based on the similarity of *two groups* in their predicted and experienced affect, not the accuracy of a *given individual's* affective forecasts.

Larsen et al. (2001) found that when anticipating future events people tend to overlook negative emotions and focus on the positive emotions, suggesting potentially differential accuracies for the prediction of positive versus negative emotions.

Other research suggests that for certain situations, *predicted and actual experiences do not coincide at all.* For example, Woodzicka and LaFrance (2001) found that in sexual harassment situations, imagined responses and actual responses differed such that imagined victims predicted feeling angry while actual victims felt fear and intimidation.

Overall, this research suggests that affective misforecasting of specific emotions can indeed occur, though its occurrence may be contingent on a set of moderating factors (some of which we explore later in this chapter).

### *Intensity of Affect*

As Figure 2.2 shows, another dimension of affective misforecasting concerns the misforecasting of *intensity.* The misprediction of intensity can be conceptualized in terms of the degree to which consumers *underpredict or overpredict* how they will feel. In Figure 2.2, for example, our consumer underpredicted how much depression and anger she would feel and overpredicted how much joy she would feel.

Considerable evidence supports the misforecasting of affective *intensity.* Moreover, the misprediction of intensity may occur for positive or negative emotions. To illustrate, Mitchell et al. (1997) compared people's affective forecast of a future positive event, for example, a three-week bicycle trip or a trip to Europe, with appraisals of emotions actually obtained on the trip. These authors found that participants' forecasted emotions were more positive than the emotions they actually experienced. Mellers (2000) found *mixed results* regarding the accuracy of the prediction of pleasure. Her *laboratory studies* revealed accuracy in the prediction of affective reactions to various outcomes, while her *real-world studies* (pregnancy and dieting) revealed an overprediction of displeasure associated with these experiences.

Gilbert, Morewedge, Risen, and Wilson (2004) found that people overestimate how much regret they will feel (misprediction of intensity). In Study 1, participants played a modified version of the TV game show "The Price Is Right." They were shown two identical sets of products and were asked to order them by price. They were allowed two different orders; with each order representing their best guess. Participants were then told to choose one of the two orders that they thought was the best arrangement. If they chose a set and it had the correct order they would win a big prize; if incorrect they would win a small prize. Half of the consumers were "experiencers" who were told that the set they chose was arranged incorrectly and that they did not win the attractive prize. These participants were told that they had lost by either a narrow or a wide margin. Participants in both conditions reported how much regret and disappointment they actually felt. The remaining half of the participants were "forecasters" who were asked to forecast how much disappointment and regret they would feel if they lost by a small margin or a wide margin. Compared to experiencers, forecasters overestimated how much regret they would feel in the narrow margin condition and overestimated how much disappointment they would feel in both the narrow and wide margin conditions. A second study replicated these results for subway riders who either forecasted or experienced missing a train by a narrow or wide margin. This overestimation of anticipated regret led Gilbert et al. (2004) to suggest that people who pay for options designed to reduce anticipated regret may be "buying emotional insurance that they don't need" (p. 346).

Buehler and McFarland (2001) asked students to indicate the letter grade they expected to receive in a class. They were then asked to predict how they would feel immediately after receiving a final grade that was one level higher, the same as, or lower than they expected. Subjects' actual feelings were monitored by a take-home questionnaire opened and completed immediately after they learned what their grade actually was. The results showed that individuals misforecast how bad they would feel from a lower grade and how good they would feel from a higher grade.

### *Duration*

Recent research on affective misforecasting concerns the misprediction of *duration.* That research indicates that individuals are *notoriously inaccurate at predicting the duration of their affective states* (Gilbert, Pinel et al., 1998; Gilbert, Driver-Linn et al., 2002). Specifically, people tend to overestimate how long they will feel bad (or good) after a negative (or positive) future event. Gilbert and colleagues refer to this bias as the *durability bias,* though they later coined the term *impact bias* to reflect the extent to which individuals overestimate the impact of a future event on affective states. Figure 2.2 provides an example of the misprediction of duration.

As evidence of the misforecasting of duration, Gilbert et al. (1998) asked untenured assistant professors to estimate how happy or sad they would be a few years after receiving or not receiving tenure at their academic institutions. Associate professors at those same institutions were also asked to indicate their current level of happiness. Although assistant professors projected that they would feel elated or devastated for getting or failing to receive tenure, and believed that their happiness or unhappiness would last a long time, there was actually no difference in the level of happiness of those at the same institution who had received or been denied tenure. Although, again, the comparison here is between two different groups of individuals, not the same individual when forecasting and experiencing emotions, these results suggest that individuals will likely overestimate the impact of tenure on the duration of feelings of happiness or unhappiness.

In another example of the misprediction of duration, Gilbert et al. (1998) asked voters to predict how happy or unhappy they would be at the outcome of the national election if their candidate won or lost. One month after the election, however, voters were just as happy as they had been before the election regardless of whether their preferred candidate won or lost.

### *Drivers of Affective Misforecasting*

Considerable research in psychology has attempted to explain *why* AMF occurs. As Figure 2.3 shows, AMF is presumed to result from a number of different biases. As shown there, some of these biases are associated with the process of *affective forecasting*—specifically (1) the representation of the future event or outcome, (2) one's imagined reaction to that outcome, and/or (3) the affective forecast itself. Others are linked to what actually happens, specifically (4) the *outcome* actually experienced or (5) the *affect generated from that experienced outcome.*

The discussion that follows mirrors Figure 2.3, and hence first describes the factors associated with the initial representation of the event. Then it moves to the imagined reaction to the outcome, the affective forecast itself, the actual outcome, and finally the affect experienced from that outcome.

#### *Factors Associated with the Initial Representation of the Event*

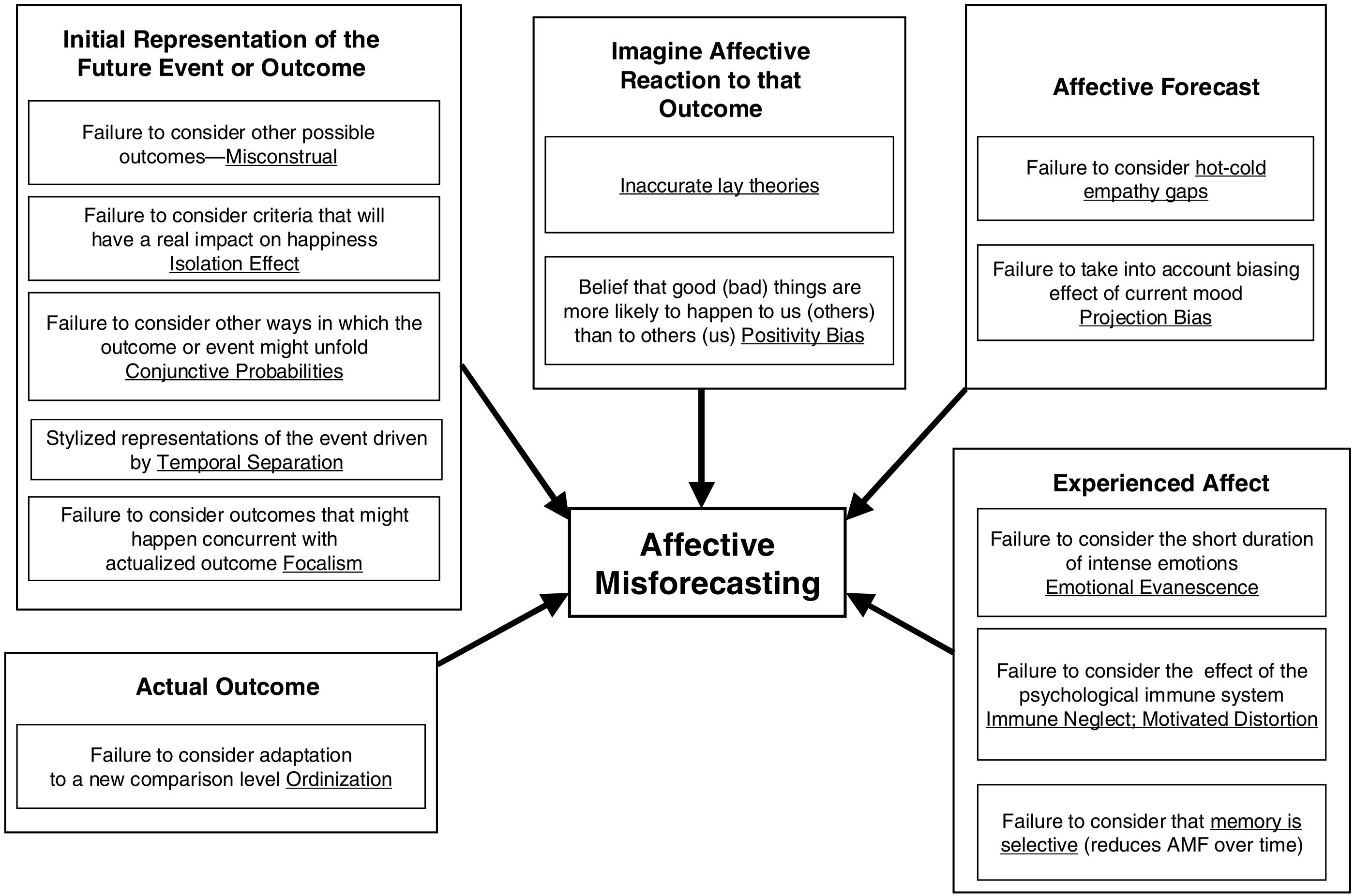
Several researchers have tied AMF to the manner in which the future outcome is represented in working memory. Biases thought to occur during this initial event representation include (a) misconstrual, (b) the isolation effect, (d) the failure to consider conjunctive probabilities, (d) temporal separation, and, (e) focalism (see Figure 2.3). We describe each in turn below.

*Misconstrual.* People often have in mind *one way* in which an outcome might turn out, and they *fail to consider other possible outcomes.* In fact, Griffin and Ross (1991) review evidence that people are unaware that their views of the future are an abstraction of reality that *they* have constructed rather than a representation of some objective reality. Thus, for example, when individuals imagine their upcoming vacation, they may not consider that their envisioned dream vacation could be ruined by rain, a fight with one's spouse, or food poisoning. Another example of misconstrual is shown in Figure 2.2 where our consumer imagines a normal birth, not considering that the actual outcome (an emergency C-section) could be different.[3]

*Isolation Effect.* The isolation effect refers to errors in affective forecasting driven by the *failure to consider criteria that will have a real impact on happiness.* Dunn, Wilson, and Gilbert (2003) illustrate this bias. College students were asked to forecast how happy they would be in one year if they lived in one dorm versus another. The authors hypothesized that students would focus on physical features that differentiated the dorms from each other and use *these* differences as a basis for predicting their future happiness. The dorms were being considered in isolated terms—in terms of their physical features, not other factors that might be considered and that might really predict happiness. After they were contacted a year later, their happiness was in reality more a function of the *social aspects* as opposed to the physical characteristics that distinguished the dorms.

*Conjunctive Probabilities.* One reason AMF may occur is that consumers *ignore the assessment of conjunctive probabilities* in their representation of the future outcome. When consumers

Figure 2.3 **Identifying the Sources of Affective Misforecasting**



think about the future, they conceptualize outcomes that are the result of a series of event co-occurrences. For example, an individual who imagines spending part of her vacation lounging in the sun on her balcony develops a scenario that includes a set of concurrent events (sunshine, a balcony, a balcony facing the sun, lounging chairs, etc.). This representation is based on a set of cumulative probabilities regarding each individual outcome. It is also contingent on her feeling relaxed on vacation, which is in turn a function of whether the plane gets off without a hitch, whether her baggage arrives at the airport, whether the hotel she wishes to stay at can still accommodate her, and so on. As Kahneman and Tversky (1982) note, however, "the cumulative probability of at least one fatal failure in the sequence of images could be overwhelmingly high, even though the probability of each individual cause of failure is negligible" (pp. 207–208). Consider as another example the consumer in Figure 2.2 who anticipates feeling joy at the birth of her baby. She may not consider the number of contingent outcomes that connect going to the hospital with the outcome of joy from childbirth. Any number of things that intervene between the act and the outcome could go wrong such as an exceedingly painful labor, bad nursing staff, an uncomfortable room, distress of the baby, or the doctor's unavailability. The occurrence of any one of these factors could alter the affect experienced from childbirth and, as such, result in AMF.

*Temporal Separation.* As shown in Figure 2.3, affective misforecasting may also arise when the time between the affective forecast and its experience is lengthy. When thinking about the distant future, people tend to create *stylized representations* of the future (Loewenstein and Schkade, 1999). When these mental images are conjured, they may be atemporal (i.e., the time the event is likely to occur is not specified) and people fail to adjust for the temporal component of the event (Friedman, 1993; Gilbert, Gill, and Wilson, 2002). Liberman and Trope (1998) describe two types of mental "construals." High-level construals involve thoughts about an event or outcome that are schematic, abstract, decontextualized, semantic, structured, and parsimonious while low-level construals involve thoughts about events or outcomes that are nonschematic, individualized, concrete, and contextualized, involve concrete actions, and present complex, rich, and detailed images. The authors predict that (a) high (vs. low) levels of construals are used when the distance between an anticipated event is far (near) and that (b) when high-level construals are used, positive outcomes seem more positive and negative outcomes seem more negative than when low-level construals are used. Thus, the time at which the outcome is imagined (in the near or distant future) can affect the intensity of the affective forecast and hence impact the magnitude of AMF.

Independent of the representation of the event but related to temporal separation, Suh, Diener, and Fujita (1996) have found that recent events have a far more powerful influence on experience than events that are in the distant past. Thus, the closer the affective forecast to the time of experience (i.e., the shorter the temporal horizon), the greater the likelihood that the experience will conform to the forecast.

*Focalism.* A final factor linked to the representation of the future event shown in Figure 2.3 is *focalism.* Wilson et al. (2000) demonstrate that affective forecasts are sometimes wrong because people fail to consider the myriad factors that may occur along with the actual outcome that may also influence their future feelings. For example, we may predict that we will feel considerable enjoyment and family bonding when swimming in the pool with family at the end of a hot summer day. However, we likely fail to consider other factors that occur at the end of the day that may also influence our feelings of enjoyment and bonding. We may not consider how tired we will be, the mosquitoes that will come out during the evening, the fact that the kids will be irritable from having spent the whole day at home, and so on. Wilson et al. (2000) label this bias "focalism" because when we think about how a future event will make us feel, we tend to focus only on that event, not the other thing that may also happen *at that time* that could alter how we may feel.

Wilson, Wheatley, Meyers, Gilbert, and Axsom (2000; see also Schkade and Kahneman, 1998) provide empirical evidence that focalism influenced the affective misforecasting of duration. They asked college students to predict how happy or sad they would feel if their team won or lost a big upcoming football game. Before they made their projections, half of the students were asked to fill out a "future diary" in which they wrote all of the things that would likely happen in the three days after the event. The theory was that getting respondents to focus on other things that might affect their feelings would minimize the affective misforecasting gap. As predicted, participants who completed the diary had less extreme predictions about how happy they would be if their team won and how sad they would be if their team lost than did participants in the no-diary condition. Relatedly, Buehler and McFarland (2001) found that individuals had more unrealistic affective forecasts regarding their feelings on Christmas Day when they focused only on the upcoming holiday and not other factors that surrounded it. Naturally, because it is often impossible to know beforehand what things are going to happen to us in the future that might affect how we feel, the impact of focalism may be quite powerful.

### *Factors Associated with the Imagined Affective Reaction to the Outcome*

Figure 2.3 shows that affective misforecasting is also tied to factors associated with the imagined affect we predict will arise from a future experience. These factors include (a) the use of inaccurate lay theories and (b) the positivity bias.

*Inaccurate Lay Theories.* We may mispredict how much pain/pleasure we are likely to feel because we hold *inaccurate theories* as to whether certain outcomes will indeed evoke specific affective reactions. If the theory is wrong, the affect we predict will arise in the future may also be wrong.

Consider, for example, how inaccurate theories about variety seeking can result in AMF. Consumers have lay theories about variety seeking (Read and Lowenstein, 1995). Specifically, they forecast a negative affective reaction to the repeated consumption of the same item and forecast that they would be happier if they chose a different item over repeated consumption occasions. However, theories about satiation are sometimes wrong. Read and Lowenstein (1995) told participants that they would be returning to the lab on three consecutive Mondays and asked them to plan a menu of which of a set of snacks they would like to have when they returned on each occasion. Subjects' menus included a variety of assorted snacks, with participants apparently using a theory that variety was better than no variety. However, when they returned to the lab, participants were often disappointed with the choice they made for themselves. For example, people who chose tortillas and cheese on their first visit predicted that they would prefer chips on the next occasion—because they would be better off seeking variety. However, these individuals were less happy with their choice (of chips) when it replaced the snack they chose on the first occasion (tortillas and cheese). Since they would have preferred their favorite snack all the time, their theory that "variety is good" was not able to predict future preferences accurately.

Conversely, consumers can also have inaccurate theories that cause them to underpredict satiation. A worked-up executive may imagine bliss at a vacation where she does nothing but read. However, she many be quite unhappy with a vacation that provides little external stimulation because she underpredicted how much variety she really needs on vacation (see also Ratner and Kahn, 1999).

People hold inaccurate theories regarding many things besides variety. McFarland, Ross, and DeCourville (1989), for example, examined the theory that many women have regarding the relationship between mood and menstruation. Although many women believe that their moods are worse during menstruation, daily measurements of mood showed that this theory was not borne out by the data.

*Positivity Bias.* Research has also shown that while individuals tend to be relatively accurate in making predictions about their *environment and others,* they tend to be remarkably biased in their predictions about *themselves,* predicting that good things are much more likely to happen to them than to other people (e.g., Matlin and Stang, 1978; Weinstein, 1980; Perloff, 1987). This phenomenon has been labeled the *optimistic or positivity* bias. A number of studies have shown that when thinking about the future individuals estimate the likelihood that they will experience a wide variety of *pleasant* (goal-congruent) events *more so than will their peers* (see Fiske and Taylor, 1991). For example, Carroll (1978) found that when subjects imagined the outcome of an upcoming football game, they were more likely to imagine their own team winning. Similar effects have been reported by Hirt and Sherman (1985) and Sherman, Zehner, Johnson, and Hirt (1983). We have a tendency to believe, for example, that we are much more likely than our peers to get a good first job, get a good salary, or have a gifted child (Weinstein, 1980). Conversely, when asked about the chances of experiencing a wide variety of *negative* (goal incongruent) events, including having an automobile accident, being victim of a crime, or being depressed, most people believe that they are *less likely* than their peers to experience such outcomes.

A focus on a positive future may incline consumers to focus on outcomes that are desirable. Unfortunately, a focus on the ideal or desirable sets up the potential for misprediction since outcomes that are desirable need not be those that are likely. As such, we would expect that the more consumers imagine desirable rather than realistic outcomes, the greater the magnitude of the affective misforecasts for goal relevant emotions.

### *Factors Associated with the Forecast of Affect*

As Figure 2.3 shows, several factors associated with the forecast of affect itself have been linked with affective misforecasting: (a) the hot-cold empathy gap and (b) the projection bias.

*Hot-Cold Empathy Gap.* Research on the *hot-cold empathy gap* proposes that people have difficulty predicting future affect if their current affective state differs from the state they will ultimately be in when the experience actually takes place. When in a “cold” (nonaffect-laden) state people often have difficulty imagining how they would feel or what they might do if they were in a “hot” state—for example, angry, hungry, in pain, or sexually excited. It may also be the case that, when in a “hot” state people frequently have difficulty imagining that they will inevitably eventually cool off (Loewenstein and Schkade, 2000). See Figure 2.4.

*Projection Bias.* The *projection bias,* also called the *presentism bias,* is said to occur at the time of forecasting and involves using present affect as a “proxy” for future feelings. Loewenstein et al. (2000) suggest that people “project” their current emotions onto the future and that a person’s immediate emotions or visceral states can have an immense influence on how they perceive their future affective states (see also Kahneman and Tversky, 1982; Schwartz, 1990; Damasio, 1994). Patrick, Fedorikhin, and MacInnis (2004) have investigated the influence of ambient mood on affective predictions and find that mood has a “coloring” influence on affective forecasting for

Figure 2.4 **The Hot-Cold Empathy Gap**

| | | **Future state** | |
|---|---|---|---|
| | | ***Cold*** | ***Hot*** |
| **Current State** | ***Cold*** | Accurate prediction of influence of affect | *Ex: Plans made after a meal to eschew dessert tomorrow*<br>Severe underestimation of the impact of effect |
| | ***Hot*** | *Ex: Shopping on an empty stomach*<br>Overprediction of influence of affect | Underestimation of the impact of affect |

neutral future events. The presentism bias explains why people who are in a good mood (those who feel happy or joyous) overestimate the probability of good outcomes, whereas those in a bad mood overestimate the probability of negative future outcomes (e.g., Nygren, Isen, Taylor, and Dulin, 1996).

Wilson and Gilbert (2003) note that there are good reasons why this projection bias is strong. “In order to [reduce the bias] people would have to be aware that their judgment is biased, be motivated to correct the bias, be aware of the precise direction and magnitude of the bias, and be able to correct their responses accordingly” (p. 361).

*Factors Associated with the Actual Outcome*

Figure 2.3 shows that at least one factor associated with the outcome itself can also be linked to affective misforecasting.

*Ordinization.* Affective misforecasting can sometimes be tied to a process called *ordinization,* or the failure to consider that novel experiences may become ordinary when they are repeated over and over. Because they become ordinary, they may fail to have the same affective impact that they had when they first occurred. For example, one might predict that winning the lottery would make one extremely happy and happy for a long time because one could buy whatever one wanted. At first, the lottery winner is indeed gleeful at the prospect of buying a grander house, better furniture, and so on. However, over time, these glee-producing experiences become ordinary, and they become the new status quo against which happiness is judged. Because they are ordinary, they fail to produce the intense positive feelings they once did. And because they are ordinary, they do not encourage feeling good for as long as anticipated. As a result, ordinization may lead to the affective misforecasting of intensity and duration.

Ordinization may work through an assimilation and accommodation process. Ordinization may also occur because individuals try to make sense out of the way they feel and invoke a hindsight bias. Specifically, an outcome is viewed as inevitable when viewed in retrospect and with hindsight knowledge—even though one would not have predicted this outcome a priori (Wilson, Gilbert, and Centerbar, 2002).

### *Factors Associated with the Experienced Affect*

Finally, Figure 2.3 shows that several factors associated with experienced affect may impact affective misforecasting. Below we consider (a) emotional evanescence, (b) immune neglect (or the operation of the psychological immune system), and (c) selective memory. The first two are predicted to enhance AMF. The last is predicted to reduce AMF.

*Emotional Evanescence.* As shown in Figure 2.3, affective misforecasting of duration and intensity may occur because consumers fail to realize how fleeting their emotional responses to outcomes are. Wilson, Gilbert, and Centerbar (2002) suggest that from an evolutionary standpoint it is adaptive for us to experience emotions for only a short period of time. Intense emotions are physiologically taxing and distract cognitive processing resources from the environment. Rapid recovery from intense emotions may also have evolutionary and adaptive significance by allowing the individual to stay focused and attentive to the immediate (and not always benign) environment. Because we do not consider how fleeting our emotions are, we are likely to overpredict how intensely and for how long we will feel good following positive outcomes and bad following negative ones.

*Immune Neglect.* One reason we may mispredict how *bad* we will feel after something negative occurs is that we do not take into account the fact that our psychology works to minimize the psychological discomfort caused by negative events. Gilbert et al. (1998) propose that people possess a "psychological immune system" about which they are not aware. Because they are not aware of it, they neglect to take it into account when making affective forecasts. As such, they overestimate the affective impact of a negative future event on their daily lives. Describing it as an *immune neglect* bias (see Figure 2.3), these authors propose that people's lack of faith in their own resiliency leads them to incorrectly expect that intense negative emotions will always last longer than less intense emotions. In fact, however, people are skilled at reconstruing what happens to them in a positive light and fail to consider the effect of the psychological immune system. This psychological immune system (PsyIS) encompasses a range of clever ways by which the human mind "ignores, augments, transforms, and rearranges information in its unending battle against the affective consequences of negative events."[4]

The PsyIS is believed to come into play when two conditions are met (Gilbert et a1., 1998):[5] (a) a sufficient amount of negative affect is experienced to activate the system, and (b) the features of the target event facilitate the operation of the PsyIS and enable it to do its job easily. Thus, based on the research by Gilbert and his colleagues, an event in which feelings are "worse than forecasted" is likely to trigger the operation of the PsyIS in order to assimilate this gap. Geers and Lassiter (2002) specify that this assimilation or "closing of the gap" is possible only when a discrepancy between the two is not noticed. If the discrepancy *is* detected, then affective experiences are contrasted from the expectation. Gilbert et al. (1998) posit that individuals are not aware of the existence of the PsyIS and thus exhibit the tendency to overestimate the duration and impact of negative feelings/experiences.

As evidence for the existence of a psychological immune system, Gilbert et al. (1998) conducted an experiment involving a mock job interview. Participants were told they would answer several interview questions, which would be viewed via videotape by a panel of (unseen) judges in the next room. Based on the job candidate's answers to the questions, the judges would accept or reject the candidate for the job. Participants were divided into two conditions. In the "easy to rationalize" condition, participants were told that only one judge would determine whether they got the job. In the "difficult to rationalize" condition, participants were told that unless the panel of judges unanimously decided to reject them they would have the job. Participants were then asked to forecast how happy or unhappy they would feel immediately after or 10 minutes following learning about whether they got the job. After making affective forecasts, participants in both conditions were told that they were rejected for the job. Actual happiness was assessed immediately and 10 minutes after the news of the rejection. All subjects were happier than they had predicted what they would feel, but interestingly, subjects in the easy to rationalize condition were happier than those in the difficult to rationalize condition. The reason is that they could use the excuse that only one person found them not right for the job as evidence that the observer was biased. In other words, their psychological immune system made them feel better by giving them a reason (a biased observer) as to why they were rejected. They could thus discount the fact that the reason they were not chosen had something to do with them.

*Selective Memory.* Although the above factors explain why affective misforecasting may occur, there are other reasons to believe that *other factors minimize AMF.* One has to do with the selective nature of memory. Take the following example relevant to Figure 2.2. Childbirth is often quite dramatic and traumatic and rarely conforms to a first-time parent's forecasts of affect. However, with time, memories of pain, depression, and anxiety are distorted, as are memories of the extent, nature, and duration of euphoria (Klaaren, Hodges, and Wilson, 1994). As such, while affective misforecasting may occur, over time selective memory distorts the experience and what one remembers becomes more and more congruent with what one had predicted. We therefore might expect that, over time, the other dimensions of affect such as the perceived intensity, direction, and duration of affect also exhibit a U-shaped pattern.

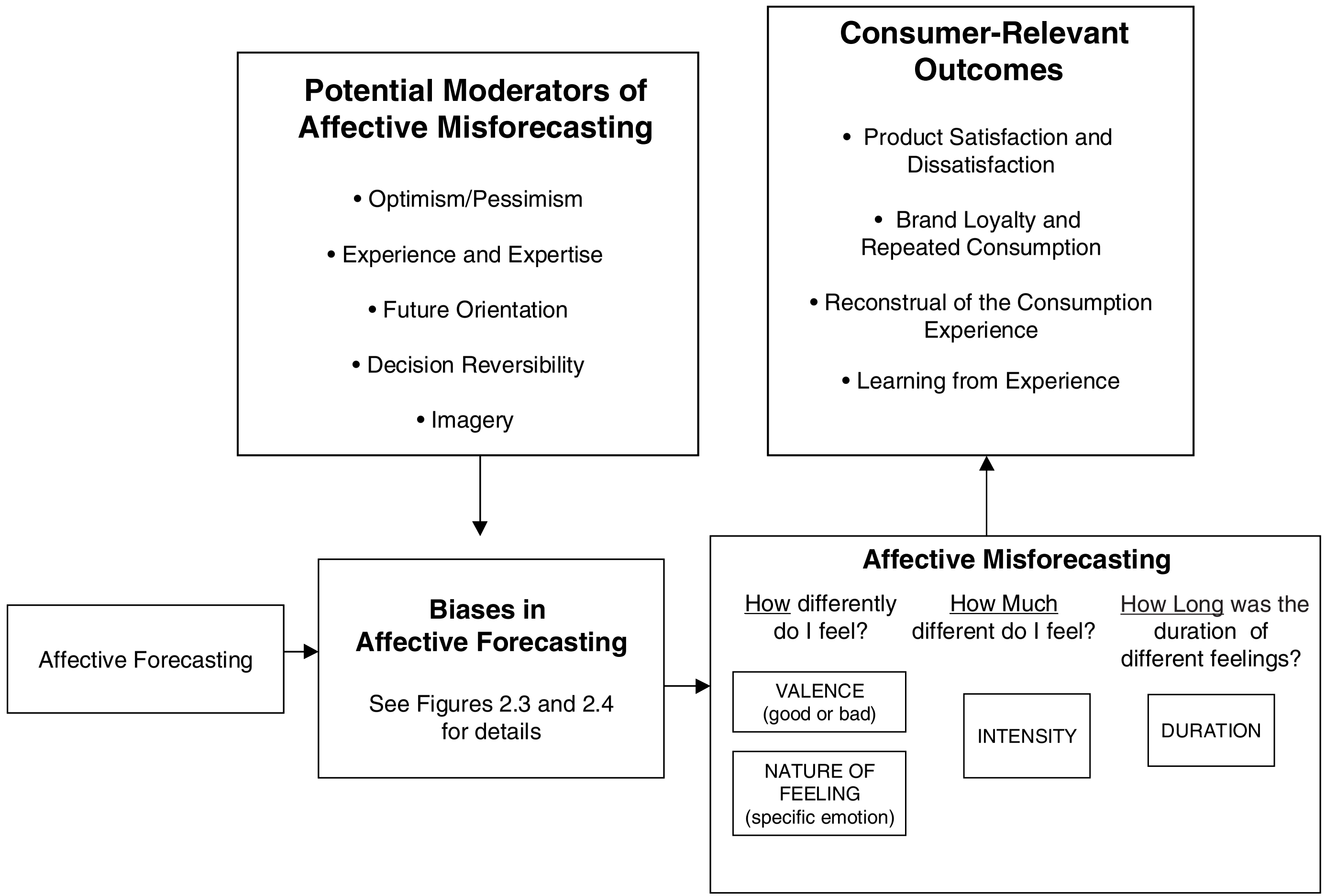
### ***The Relevance of AMF: Why Should We Care?***

Affective misforecasting is potentially important to a number of marketing-relevant outcomes. Interestingly, the impact of AMF on these outcomes represents considerable opportunity for research in our field as we have only begun to examine its potential impact. Below we consider the impact of AMF on five outcomes as shown in Figure 2.5: (a) product satisfaction and dissatisfaction judgments, (b) variety seeking, (c) brand loyalty and repeated consumption, (d) the reconstrual of the consumption experience, and (e) learning from experience.

#### *Product Satisfaction/Dissatisfaction*

Since choice is predicated on forecasted affect, and since forecasted and experienced affect often diverge and result in affective misforecasting (AMF), it is critical to examine how and whether AMF impacts consumer satisfaction. Examining the impact of AMF on satisfaction is further underscored by the relevance of satisfaction to critical marketing outcomes such as brand loyalty,

Figure 2.5 **Affective Misforecasting and Its Relevance to Consumer Behavior and Marketing**



willingness to pay a price premium, repeat purchase and word-of-mouth behavior, and so on.

Patrick, MacInnis, and Park (2004) provide one of the first accounts of the impact of AMF on product satisfaction/dissatisfaction. In their research, consumers were asked to make predictions about a future consumption experience. Later, consumers experienced feelings that were either "better than" or "worse than" forecasted. An analysis of the effect of AMF (and the actual affect experienced) on satisfaction showed that (a) affective misforecasting did affect consumers' satisfaction and that (b) the influence of misforecasting on satisfaction was above and beyond that accounted for by experienced affect or any performance-related disconfirmation of expectations. Interestingly, the impact of AMF on satisfaction was asymmetric—it influenced satisfaction only when feelings were "worse than" forecasted but not when they were "better than" forecasted. The authors also demonstrate that the reason AMF affects satisfaction when outcomes are worse than expected is that consumers elaborate on why their feelings might have been worse than predicted. This elaboration caused them to focus on product factors that were responsible for the negative feelings. The attribution of responsibility to the product reduced product satisfaction. The existence of the elaboration-based route was further supported by results showing that AMF had no impact on satisfaction when consumers were given a task that inhibited their opportunity to engage in elaboration.

Affective misforecasting may also be relevant to the domain of consumers' satisfaction with their decisions to seek variety. Since consumers often have inaccurate theories about satiation, they may mispredict how they will feel with a choice predicated on a theory about variety seeking. One wonders whether AMF resulting from inaccurate theories about variety not only impacts consumers' satisfaction with their *choice* (e.g., I wish I had chosen tortillas and cheese instead of chips) but also carries over to affect their dissatisfaction with the *product* (chips).

### *Brand Loyalty and Repeated Consumption*

Since affective misforecasting has an impact on satisfaction, it is logical to infer that it would consequently influence brand loyalty and repeated consumption. It seems obvious that when feelings are worse than forecasted, brand loyalty will be negatively influenced and consumers will stop or lower their use of the product on subsequent consumption occasions. However, as shown below, the link between dissatisfaction and reduced repeat purchase likelihood is contingent on accurate memory for the actual affective experience. As shown earlier, however, memory is selective, and the affect linked to memory of the experience may become distorted over time.

Klaaren, Hodges, and Wilson (1994) asked participants to forecast how good they thought an upcoming vacation would make them feel. The same participants were queried about their vacation experiences one week and then again six weeks after the vacation. Subjects' evaluations of the vacation at the six-week interval were a function of both their evaluation of the experience one week out and their affective forecasts. As such, long-term evaluations of the experience and the desire to repeat it were affected not only by the experience but also their affective forecasts.

Why might affective forecasts affect not only choice but also repeat purchase likelihood, despite potential initial dissatisfaction? Klaaren, Hodges, and Wilson (1994) propose several potential reasons; however, their data were most consistent with the *reinterpretation hypothesis.* That hypothesis posits that with the passage of time the actual experience is reinterpreted in a direction consistent with the initial forecast. Thus, either the meaning of the experience is altered (e.g., it wasn't "boring"—it was "educational"), or aspects of the experience are reweighted so that negative feelings assume less importance and positive ones greater importance (e.g., "yes, the long lines at their airport were a bit annoying, but the place we went to was so beautiful it was worth it"). Notably, however, not all of their findings were consistent with this explanation.

*Reconstrual of the Consumption Experience*

A related issue associated with repeated consumption is the impact of affective misforecasting on the way in which a consumption experience is itself construed after it has occurred. Although we are aware of no research that examines the impact of affective misforecasting on the reconstrual of a consumption experience, by drawing on related literature we posit that the affect linked to a consumption experience may be construed to be more similar to or more different from forecasted affect based on the goals the consumer desires to achieve. For instance, one might feel unhappy with the purchase of a piece of furniture but refuse to accept that one made a mistake, construing the purchase as positive despite the negative feelings. This *reconstrual* of events to "fit" with one's consumption goals or motivations may be considered one of the psychological mechanisms that comprise the Psychological Immune System (Gilbert et a1., 1998) described earlier.

*Learning from Experience*

Finally, AMF has implications for the domain of whether and to what extent consumers learn from experience (cf., Hawkins and Hoch, 1992; Hoch and Deighton, 1989; Hutchinson and Alba, 1991; Johnson and Russo, 1984). Wilson et al. (2001) suggest that in order for people to learn from their past affective experiences, three criteria must be satisfied: One is the *mental effort criterion;* people need to make an effort to compare past experiences with future ones instead of thinking of the future event in isolation. Sole focus on a future event without thinking about similar past events results in less accurate affective forecasts (Buehler and McFarland, 2001) as explained in our discussion of focalism. Second is the *applicability criterion;* if people do make the effort to consult the past, they need to decide which past event is most applicable. Third is the *accuracy criterion;* if people do find an applicable event and decide to invest the effort to compare these events, they need to be able to recall or reconstruct these events accurately. However, people's memory for affective states, especially with regard to the intensity and frequency, is typically relatively poor (Fredrickson and Kahneman, 1993; Levine, 1997; Levine and Safer, 2002).

In a series of studies, Wilson et al. (2001) demonstrated that experience with a negative event (but not with a positive event) may improve the accuracy of one's affective forecasts, but the extent to which people learn from their affective forecasting errors may be limited. Gilbert and Wilson (2000) posit that people do not learn that their theories are incorrect because (a) they do not pay enough attention to the relationship between the theory and the outcome to realize that they are wrong or (b) the experiences are ambiguous and do not provide clear disconfirming evidence that the theory is wrong.

***Factors Potentially Moderating the Extent of AMF***

Although opportunities abound for examining the impact of AMF on evaluative judgments such as postconsumption satisfaction and learning outcomes such as learning from experience, equally interesting and important opportunities exist to understand factors that may moderate the impact of AMF on the outcomes described above. In the following, we consider whether and why factors such as (a) optimism, (b) expertise, (c) future orientation, (d) decision reversibility, and (e) imagery may moderate the impact of AMF on satisfaction, other judgments and learning.

*Optimism/Pessimism*

Fairly little research has examined whether individual differences influence affective forecasting and misforecasting. What little that exists, however, is interesting. Geers and Lassiter (2002) examine the moderating role of optimism/pessimism on the relationship between affective forecasts and affective experiences. They find that pessimists are most sensitive to situations when actual feelings diverge from forecasted feelings and thus often contrast their actualized affective reactions with their forecasted affective reactions. On the other hand, optimists are less likely to notice the deviation of an experience from a forecast, and they often assimilate experienced affect with their affective forecasts. This finding would suggest that the impact of AMF on learning from experience is moderated by individual differences in optimism and pessimism.

*Experience/Expertise*

Research has not examined the role of expertise on the nature and extent of AMF. However, given prior research suggesting that little learning tends to occur from past AMF encounters, it is quite possible that affective misforecasting is immune to differences across individuals in expertise. Such a finding would be interesting in light of the fact that expertise has been found to be a major factor affecting consumer information processing, and because affective forecasting may depend on elaborated information processing. One possible explanation for this discrepancy is that consumers' perceived experience and their actual knowledge often do not coincide, and this gap may account for the discrepancy. Specifically, Park, Mothersbaugh, and Feick (1994) suggest that how much one thinks one knows versus how much one actually knows has a different impact on information search and processing. As long as consumers perceive a high degree of self-assessed knowledge about the future outcome, they may not be as attentive to their past affective misforecasting as they should be.

Related to experience and expertise is age. Does the extent or nature of AMF and its impact on the outcomes described in Figure 2.5 change with experience or age? Few studies have examined these issues, but what does exist is provocative. Wilson, Gilbert, and Salthouse (2001; cited in Wilson and Gilbert, 2003) examined this question, though more in the realm of affective forecasting than misforecasting. When asked to report on how long it would take for their happiness or unhappiness with a given outcome to wear off, older consumers (those over age 60) predicted that *it would take less time for the emotion associated with both major and minor outcomes to wear off.* This finding suggests that older (and potentially more experienced) consumers would be less likely to fall victim to AMF caused by emotional evanescence (see Figure 2.3). Looking at predicted and experienced outcomes, however, Carstensen, Pasupathi, Mayr, and Nesselroade (2000) found that it *actually took consumers older than age 60 longer to recover* from negative experiences than it did younger consumers. Clearly, additional work on the potentially moderating role of age on AMF and the outcomes that accrue from it is warranted.

*Future Orientation*

Individuals and cultures differ in the extent to which they think about and consider the future. Consistent with this notion, Strathman et al. (1994) propose an individual difference construct called *consideration of future consequences*. Individuals who are high in consideration of future consequences think about the impact of their current behavior on their future and tend to use long-term goals as a guide for their behavior. It is possible that individuals who are high in the consideration of future consequences differ systematically from those low in future consequence in the nature and extent of AMF. On the one hand, those who consider future consequences may be more prone to AMF as they may be more likely to engage in elaborated imagery processing that involves the future and goal-relevant affective experiences imagined to occur in the future. On the other hand, Strathman et al. (1994) propose that individuals who are high in consideration of future consequences may be more attuned to a discrepancy between imagined and experienced outcomes. They may thus feel that they have learned something and to incorporate this learning into future affective forecasts, reducing the likelihood of AMF in the future.

*Decision Reversibility*

Gilbert and Ebert (2002) propose that when an unpleasant outcome occurs, an individual's first action is to try to change that outcome. For example, if a person buys a product thinking that it will make her feel good but later finds out that it does not, her first action will be to try to undo the situation and take the product back to the store. However, when the option of undoing the situation is not possible (the decision is irreversible), the individual will instead try to reconstrue or reevaluate the outcome, perhaps convincing herself that it is perhaps not as bad as she initially felt. It is possible that when the decision is reversible we see evidence of AMF, and this AMF stimulates action (returning the product). When the decision is not reversible, AMF may also occur initially, but feelings associated with the forecast (this product does not make me as happy as I thought it would) are erased because the consumer knows the outcome of the situation cannot be changed. The consumer therefore tries to reinterpret the outcome in a manner that is more consistent with the outcome he or she had forecasted. Hence, reconstrual of the consumption experience may be more likely when the decision is irreversible than reversible.

*Outcome Versus Process Focused Imagery*

Taylor, Pham, Rivkin, and Armor (1998) suggest that imagery processing can involve at least one of two foci: (a) the *outcome* presumed to arise from an imagined future and (b) the *process* that may be invoked to achieve an outcome. Although research has not examined outcome or process-focused imagery in the context of affective misforecasting, it is possible that AMF is reduced when imagery is process versus outcome focused. The reason is that a focus on the process of goal attainment may direct attention away from the ultimate anticipated affect and focus attention on situational, personal, or social factors involved in the process of goal achievement that may impact the imagined outcome's occurrence. Hence, process-focused imagery may reduce the extent to which consumers engage in misconstrual, the isolation effect, or focalism. Attention to these process-oriented factors may reduce the perceived intensity of the forecasted affect and the confidence with which this forecast is held because it alerts consumers to the possibility of other outcomes and their potential affective consequences, or cues them to the presence of affect in the process itself that may temper their forecasted affect. This alteration of forecasted affect may minimize the subsequent gap between what was forecasted and eventually experienced.

In this section, we have discussed the variety of sources of error in affective forecasting leading to affective misforecasting. We conclude this review with a discussion of the implications of affective forecasting for marketing practice followed by a discussion of some additional for future research.

### Normative Issues Regarding Affective Forecasting in Marketing Practice

Although the bulk of this chapter has considered affective forecasting and misforecasting and its effects, additional research is warranted on the normative implications of affective forecasting; that is should marketers induce affective forecasting, and if so, when?

Earlier, we argued that forecasts of positive affect should enhance consumers' abilities to cope with negative consumption experiences as well their abilities to delay gratification and engage in self-regulatory practices. Since such outcomes are generally desirable and have positive implications for consumer welfare, the encouragement of positive affective forecasts should be generally desirable.

We also indicated, however, that affective forecasting can affect choice and decision making (see Figure 2.1) and satisfaction with consumption choices once they are experienced (see Figure 2.5). The relative impact of affective forecasting on choice and satisfaction leads to some rather complex predictions about the normative appropriateness of inducing affective forecasting. Figure 2.6 illustrates these complexities, showing a typology of types of goods. *Approach goods* are those products that induce forecasts of positive affect (e.g., buying a new car, going on vacation, or buying skin cream designed to reduce wrinkles). Such goods enhance choice likelihood because they induce affective forecasts of positive affect following product purchase or consumption. *Avoidance goods* are products that induce forecasts of negative affect (such as going to the dentist, going for a college interview, or having a medical diagnostic test). Such goods reduce choice likelihood by inducing forecasts of negative affect.

The rows of Figure 2.6, however, suggest that these choice implications should also be crossed with the satisfaction implications of using these goods and experiencing the affect that accrues from their use. As shown there, goods can also be described according to whether they are *search, experience*, or *credence goods*. According to Nelson (1970), search goods are goods whose attributes are concrete and searchable prior to choice. Because such goods involve search components, consumers should have greater opportunity to make an accurate prediction as to how those goods and the attributes they entail will make them feel. Because these goods are comprised of concrete attributes, consumers should also be able to readily evaluate how well the product did in meeting performance expectations.

With search goods, inducing forecasts of positive affect is useful as long as product usage is also positive (see cell A of Figure 2.6). If product usage is negative, positive affective forecasts are likely to be violated, leading to overprediction of positive affect, underprediction of negative affect, and a resultant decline in satisfaction. Thus, with search goods, affective forecasting is most beneficial when the good is an approach good and the product creates affective responses that match or exceed those forecasted.

A second case when the affective forecasting of search goods might be appropriate is with avoidance goods whose performance qualities lead consumers to underpredict how good they will feel from the product and overpredict how bad they will feel from the product (see cell H in Figure 2.6). Although these avoidance goods reduce choice likelihood, the overprediction of negative affect and the underprediction of positive affect will likely lead consumers to feel satisfied with the product as affective expectations were violated and resulted in a positive disconfirmation.

A similar prediction is made for experience goods—those goods for which the outcome of the consumption experience is unknown prior to purchase and can only be discerned through usage (see cells D and K in Figure 2.6). Many hedonic products (e.g., tasting orange juice, getting a massage) or experiential products (e.g., going to a play) are of this type. Although

Figure 2.6 **When Marketers Should Induce Affective Forecasting**

| | **Search Good** | | | **Experience Good** | | | **Credence Good** |
|---|---|---|---|---|---|---|---|
| Opportunity to make an accurate prediction | High | | | Low | | | Low |
| Opportunity to evaluate the actual experience | High | | | High | | | Low |
| *Actual Experience* | + | 0 | – | + | 0 | – | Can't evaluate |
| **Approach Good** (e.g., going on vacation)<br><br>Forecast of positive affect; enhanced choice likelihood | *A*<br>√ (C)<br>0 (S) | *B* | *C* | *D*<br>√ (C)<br>0 (S) | *E* | *F* | *G*<br>√ (C)<br>√ (S) |
| **Avoidance Good** (e.g., going to the dentist)<br><br>Forecast of negative affect; reduced choice likelihood | *H*<br>– (C)<br>√(S) | *I* | *J* | *K*<br>– (C)<br>+ (S) | *L* | *M* | *N* |

C = choice; S = satisfaction

experience goods lead to the same predictions regarding the normative appropriateness of marketers' inducements of affective forecasts, what may differentiate search and experience goods is the confidence with which the affective forecast is held and hence the downward risk to a disconfirmation of forecasts of positive experiences. Because the affective forecast may be held with less confidence with experience goods, consumers' overprediction of positive affect and underprediction of negative affect may have a less significant impact on satisfaction than is the case with search goods.

The normative appropriateness of inducing affective forecasts for experience goods is also contingent on marketers' capacities to control the nature of the consumption experience. When the outcome of the experience (e.g., a trip to Hawaii) is contingent not only on the marketer (e.g., the hotel) but also a set of other service providers (the airline, transportation companies, restaurants, entertainment options), there is greater potential for variation in actualized experiences by consumers. In such cases, inducing affective forecasting of positive affect may be more risky than is the case when the marketer can solely control the nature of the experienced outcome.

With credence goods, it would appear that marketers are always in a good position to induce positive affective forecasting as long as the good is an approach good (see cell G in Figure 2.6). Not only will such inducements enhance choice probability, but the fact that consumers have limited capacities to discern the true nature of the experience means that they will likely impute a correspondence between their predicted and experienced affect and not become dissatisfied with the consumption outcome.

## Directions for Future Research

The present chapter reviewed the literature on affective forecasting and misforecasting and articulated the relevance of these concepts to marketing and consumer behavior. As revealed by this review, much has been learned about these two concepts, though, as also indicated, numerous research issues can be raised. Although our discussion has identified many exciting areas for future research, we end our discourse with an examination of several additional (nonexhaustive) issues.

First, we have identified several different processes by which affective forecasts may arise: schema-triggered affect, schema-triggered affect adjustment, affect construction, probabilistic processes, and goal-based affect. Beyond finding evidence for each of these processes, future research might also examine the effect of these processes on the nature and extent of affective *misforecasting*. For example, since affect construction (and perhaps the goal-based affect) focuses on process, we may expect systematic differences compared to cases where affect is schema based, and outcome-focused. The reason is that a focus on the process of goal attainment may direct attention away from the ultimate anticipated affect and shift attention to those situational, personal, or social factors involved in the process of goal achievement that may affect the imagined outcome. Attention to process-oriented factors may reduce the perceived intensity of the forecasted affect and the confidence with which this forecast is held because it alerts consumers to the possibility of other outcomes and their potential affective consequences, or cues them to the presence of affect in the process itself. This attention to process-related factors may temper forecasted affect and hence minimize the subsequent gap between what was forecasted and eventually experienced, thus reducing AMF. In contrast, schema-based affect may make people less analytical, less attentive and evaluative, and possibly more impulsive in their decision process and lead to more gaps between forecasted and experienced affect (AMF).

In addition, future research might examine whether and to what extent these different processes are tied to the different types of biases identified in Figure 2.3. For example, focalism may be more prevalent when affective forecasting is based on schema-triggered affect than on probabilistic processes, as the former process involves little elaboration of other possible outcomes. Similarly, the failure to consider conjunctive probabilities may be most prevalent when affective forecasting is based on affect construction, as imagery processing tends to evoke a gestalt scenario, not the contingent outcomes that would yield this scenario.

Additional questions concern the affective forecasting of specific emotions. Emotion theorists have identified a range of emotional states that are differentiated on a number of dimensions. Questions arise as to whether or not different biases related to affective forecasting and AMF are activated, depending on the valence and nature of the forecasted emotion. Research on the positivity bias described above suggests that people are more predisposed to positive future orientation than to negative future orientation. They may thus develop well-structured memory schemata about positive events, including product or service consumption. The existence of these schemata may make people more susceptible to the above-mentioned biases associated with outcome-focused affect forecasting. The extent of this bias may, however depend on the specific emotion involved. Consider, for example, the potential differential misforecasting of ecstasy versus relaxation in the context of a vacation. Since relaxation is more tightly linked to the schema of a vacation than is ecstasy, it may be more prone to AMF as it is immediately linked to the future experience. It is also interesting to explain how affective forecasting of mixed emotions (e.g., glee yet sadness from college graduation) occurs and understand how such forecasting impacts consumer behavior. How one forecasts such emotions and what effect they have on consumer information processing, choice processes, repeat purchases, and the like, as well as the extent of misforecasting have not been examined in previous research.

Interesting questions can also be asked about the role of anticipated affect in consumers' choice of products involving tradeoffs. For example, in the context of product choice, consumers are likely to anticipate which types of emotions they may experience in choosing between a more hedonic/aesthetically pleasing option (e.g., enrolling for a fun/interesting class) versus a more functional/utilitarian one (e.g., enrolling for a more serious/useful class). The relative intensities of anticipated guilt with not enrolling for a serious/useful class versus boredom or even anxiety (if the work required is too high) associated with that class may affect whether serious or fun class is selected. The current literature on how difficult tradeoffs are resolved has been restricted to experienced affect (e.g., Luce, Payne, and Bettman, 1999). It is possible that anticipated affect plays a significant role in impacting how tradeoffs are made for future decisions.

To what extent do consumers engage in affective forecasts of others' experiences (literature on gift-giving and imagined emotional reactions of others to one's gift), and do these affective forecasts differ from the forecasts that exist for the self? Igou and Bless (2002) find that when making affective forecasts, individuals predict a longer duration of negative (but not positive) affect for others than for themselves. One reason could be that consumers have less knowledge about the psychological immune system of others. Another possible reason could be that individuals exhibit an optimistic bias and hence believe that prolonged negative outcomes are less likely for them than for others. In addition, affective forecasting of others may also offer an alternative explanation to the motive underlying conspicuous consumption. Rather than one's own desire to express one's self image to others, conspicuous consumption may be motivated more by one's specific forecasting of others' affective reactions to his or her consumption. Assessing others' emotional reactions and judging the potential gap between the initial expectation and their experienced affect may well involve a process that differs from affective forecasting of one's own feelings.

Additional questions concern the role of self-protection in affective forecasting. Do people regulate their affective forecasts so as to make them not too positive to prevent disappointment but not too negative to reduce motivation? Do we possess a regulatory mechanism (a sort of affective thermostat) that prevents us from extreme forecasts? Do we engage in "self-handicapping" (Tice and Baumiester, 1984; Rhodewalt et a1., 1991) when making affective forecasts in order to protect ourselves from ego-damaging future outcomes? It is also interesting to consider that although use of the psychological immune system may protect consumers from affective misforecasts, that same system may leave the consumer more vulnerable to repeating the same mistake in the future.

Finally, it is interesting to consider the potential role of culture on affective forecasting and misforecasting. Patrick (2003) suggests that one's view of the future has cultural roots and that cross-cultural differences may explain differences in the reliance on affective forecasting as an input in decision making across cultures. That research examines the differences in affective forecasting of "ego-focused" versus "other-focused" emotions among people from individualist versus collectivist cultures and the mediating role of self-construal in the cross-cultural prediction of "ego-focused" versus "other-focused" emotions. Future research on AMF and culture may yield very provocative results.

## Conclusions

This review describes the phenomena of affective forecasting and misforecasting, the relevance of these constructs for consumer behavior, and their antecedents and consequences as well as the moderating factors that influence the relationship between these variables.

In sum, this review of the emerging research on affective forecasting and misforecasting is intended to comprehensively describe the current state of the literature at this time, to integrate the various findings as they relate to consumer behavior, and, finally to suggest a future research agenda for research in this domain of inquiry.

## Notes

1. Loewenstein considers visceral states to be a broader category than emotions. The former encompasses negative emotions (anger, fear, jealousy), drives (hunger, sex, curiosity), and feeling states (pain, drug cravings) and involve the removal of an aversive state.
2. These authors therefore propose a boundary condition on the projection bias (Loewenstein et a1., 2000) discussed later in the chapter.
3. Although the isolation effect, conjunctive probabilities, temporal separation, and focalism are shown as separate from misconstrual in Figure 2.3, it is possible that these biases are actually *determinants* of misconstrual.
4. Many psychologists have noted that people are adept at subjectively optimizing their outcomes. Some of the strategies/methods used to enable this optimization that constitute the PsyIS are ego-defense, positive illusions, rationalization, dissonance reduction, self-serving attributions, self-enhancement, self-justifications, self-affirmations, motivated reasoning, and selective perception.
5. Gilbert and Ebert (2001) suggest that the psychological immune system is like cognitive dissonance but differs from dissonance in several respects. First, unlike dissonance, the psychological immune theory suggests increased satisfaction with the product when change is not possible. Second, consumers would not anticipate this difference and would therefore prefer outcomes that are changeable.

## References

Andersen, S.M., and J.E. Lyon. (1987) "Anticipating Undesired Outcomes: The Role of Outcome Certainty in the Onset of Depressive Affect." *Journal of Experimental Social Psychology,* 23 (September), 428–443.

Anderson, C.A. (1983) "Imagination and Expectation: The Effect of Imagining Behavioral Scripts on Personal Intentions." *Journal of Personality and Social Psychology,* 45 (2), 293–305.
Armor, D.A., and S.E. Taylor. (1998) "Situated Optimism: Specific Outcome Expectancies and Self-regulation." In *Advances in Experimental Social Psychology*, ed. M.P. Zanna, vol. 30, pp. 309–379. New York: Academic Press.
Bagozzi, R.P., and D.J. Moore. (1994) "Public Service Advertisements: Emotions and Empathy Guide Prosocial Behavior." *Journal of Marketing,* 58(January), 56–70.
Bagozzi, R.P., H. Baumgartner, et al. (1998) "Goal-Directed Emotions." *Cognition and Emotion,* 12 (1), 1–26.
Bagozzi, R.P., H. Baumgartner, R. Pieters, and M. Zeelenberg. (2000) *The Role of Emotions in Goal-Directed Behavior.* In *The Why of Consumption: Contemporary Perspectives on Consumer Motives, Goals, and Desires,* ed. S. Ratneshwar, D. Mick, and C. Huffman, pp. 36–58. New York: Routledge.
Bandura, A. (2001) "Social Cognitive Theory: A Genetic Perspective." *Annual Review of Psychology,* 52, 1–26.
Baron, J. (1992) "The Effect of Normative Beliefs on Anticipated Emotions." *Journal of Personality and Social Psychology,* 63 (2), 320–330.
Bell, D.E. (1982) "Regret in Decision Making Under Uncertainty." *Operations Research,* 30(5), 961–981.
Bentham, J. (1789)[original publication date]. *The Principles of Morals and Legislation.* New York: Macmillan, 1948.
Buehler, R., D. Griffin, et al. (1994) "Exploring the Planning Fallacy: Why People Underestimate Their Task Completion Times." *Journal of Personality and Social Psychology*, 67 (3), 366–381.
Buehler, R., and C. McFarland. (2001) "Intensity Bias in Affective Forecasting: The Role of Temporal Focus." *Personality and Social Psychology Bulletin*, 27 (11), 1480–1493.
Cadotte, E., R. Woodruff, et al. (1987) "Expectations and Norms in Models of Consumer Satisfaction." *Journal of Marketing Research,* 24 (August), 305–314.
Carroll, J. (1978) "The Effect of Imagining an Event on Expectations for the Event: An Interpretation in Terms of the Availability Heuristic." *Journal of Experimental Social Psychology*, 14 (1), 88–96.
Carstensen, L.L., M. Pasupathi, U. Mayr, and J.R. Nesselroade. (2000) "Emotional Experience in Everyday Life Across the Adult Life Span." *Journal of Personality and Social Psychology*, 79 (4), 644–655.
Chew, S.H., and J.L. Ho. (1994) "Hope: An Empirical Study of Attitude Toward the Timing of Uncertainty Resolution." *Journal of Risk and Uncertainty*, 8 (May), 267–288.
Crawford, M.T., A.R. McConnell, et al. (2002) "Reactance, Compliance and Anticipated Regret." *Journal of Experimental Social Psychology*, 38 (1), 56–63.
Damasio, A.R. (1994) *Descartes Error.* New York: HarperCollins.
Dunn, E.W., T.D. Wilson, and D.T. Gilbert. (2003) "Location, Location, Location: The Misprediction of Satisfaction in Housing Lotteries." *Personality and Social Psychology Bulletin* 29 (11), 1421–1432.
Edell, J. A. and M. C. Burke (1987) "The Power of Feelings in Understanding Advertising Effects." *Journal of Consumer Research* 14(December), 421–433.
Fiske, S.T., and M.A. Pavelchak. (1986) "Category-based Versus Piecemeal-based Affective Responses: Developments in Schema-triggered Affect." In *Handbook of Motivation and Cognition: Foundations of Social Behavior*, ed. R.M. Sorrentino and T.E. Higgins, pp. 167–203. New York: Guilford Press.
Fiske, S.T., and S.E. Taylor. (1991) *Social Cognition.* New York: McGraw Hill.
Folkes, V.S., I.M. Martin, et al. (1993) "When to Say When: Effects of Supply on Usage." *Journal of Consumer Research* 20 (13), 467–478.
Frederick, S., and G. Loewenstein. (1999) "Hedonic Adaptation." In *Well-being: The Foundations of Hedonic Psychology*, ed. E.D.D. Kahneman and N. Schwartz, pp. 302–329. New York: Russell Sage Foundation.
Fredrickson, B.L., and D. Kahneman. (1993) "Duration Neglect in Retrospective Evaluations of Affective Episodes." *Journal of Personality and Social Psychology*, 65 (1), 45–55.
Friedman, W.J. (1993) "Memory for the Time of Past Events." *Psychological Bulletin*, 113 (1), 44–66.
Geers, A.L., and G.D. Lassiter. (2002) "Effects of Affective Expectations on Affective Experience: The Moderating Role of Optimism-Pessimism." *Personality and Social Psychology Bulletin*, 28 (8), 1026–1039.
Gilbert, D.T., R.P. Brown, E.C. Pinel, and T.D. Wilson. (2000) "The Illusion of External Agency." *Journal of Personality and Social Psychology*, 79 (5), 690–700.
Gilbert, D.T., E. Driver-Linn, and T.D. Wilson. (2002) "The Trouble with Vronsky: Impact Bias in the

Forecasting of Future Affective States." In *The Wisdom in Feeling: Psychological Processes in Emotional Intelligence*, ed. L.F. Barrett and. P. Salovey, pp. 114–143. New York: Guilford Press.

Gilbert, D.T., and J.J. Ebert (2002) "Decisions and Revisions: The Affective Forecasting of Changeable Outcomes." *Journal of Personality and Social Psychology*, 82 (4), 503–514.

Gilbert, D.T., M.J. Gill, and T.D. Wilson. (2002) "The Future Is Now: Temporal Correction in Affective Forecasting." *Organizational Behavior and Human Decision Processes*, 88 (1), 430–444.

Gilbert, D.T., M.D. Lieberman, C.K. Morewedge, and T.D. Wilson. (2004) "The Peculiar Longevity of Things Not So Bad." *Psychological Science*, 15 (1), 14–19.

Gilbert, D. T., Morewedge, C. K., Risen, J. L., and Wilson, T. D. (2004) "Looking Forward to Looking Backward: The Misprediction of Regret." *Psychological Science,* 15 (5), 346-350.

Gilbert, D.T., E.C. Pinel, T.D. Wilson, S.J. Blumberg, and T. Wheatley. (1998) "Immune Neglect: A Source of Durability Bias in Affective Forecasting." *Journal of Personality and Social Psychology*, 75 (3), 617–638.

Gilbert, D.T., and T.D. Wilson. (2000) "Miswanting. Some Problems in the Forecasting of Future Affective States." *Thinking and Feeling: The Role of Affect in Social Cognition*, ed. J. Forgas, pp. 178–197. Cambridge: Cambridge University Press.

Griffin, Dale W. and Lee Ross. (1991) "Subjective Construal, Social Inference and Human Misunderstanding." In *Advances in Experimental Social Psychology,* Vol. 21, ed. M.P. Zanna. New York: Academic Press

Griffin, Dale W., David Dunning, and Lee Ross (1990), "The Role of Construal Processes in Overconfident Predictions About the Self and Others." *Journal of Personality and Social Psychology*, 59 (6), 1128–39.

Groopman, J. (2004), *The Anatomy of Hope: How People Prevail in the Face of Illness*. New York: Random House.

Hawkins, S.A., and S.J. Hoch. (1992) "Low-Involvement Learning: Memory without Evaluation." *Journal of Consumer Research*, 19(2), 212–226.

Hirt, E.R., and S.J. Sherman. (1985) "The Role of Prior Knowledge in Explaining Hypothetical Events." *Journal of Experimental Social Psychology*, 21 (6), 519–543.

Hoch, S.J., and J. Deighton. (1989) "Managing What Consumers Learn from Experience." *Journal of Marketing*, 53 (April), 1–20.

Hoch, S.J., and G.F. Loewenstein. (1991) "Time-Inconsistent Preferences and Consumer Self-Control." *Journal of Consumer Research*, 17 (4), 492–507.

Holbrook, M.B., and R. Batra, (1987) "Assessing the Role of Emotions as Mediators of Consumer Responses to Advertising." *Journal of Consumer Research*, 14 (December), 404–420.

Howard, D.J., and C. Gengler. (2001) "Emotional Contagion Effects on Product Attitudes." *Journal of Consumer Research*, 28 (September),189–201.

Hutchinson, J.W., and J.W. Alba. (1991) "Ignoring Irrelevant Information: Situational Determinants of Consumer Learning." *Journal of Consumer Research*, 18 (December), 325–346.

Igou, E.R., and H. Bless. (2002) My Future Emotions Versus Your Future Emotions: The Self-Other Effect in Affective Forecasting. Working paper, University of Mannheim.

Isen, A.M. (1999) "Positive Affect and Decision Making." In *Handbook of Emotions*, ed. M. Lewis and J.M. Haviland-Jones, pp. 417–435. New York: Guilford Press.

Johnson, M.K., and S.J. Sherman. (1990) "Constructing and Reconstructing the Past and the Future in the Present." In *Handbook of Motivation and Cognition*, vol. 2, ed. E. T. Higgins and R. Sorrentino, pp. 482–526. New York: Guilford Press.

Kahneman, D., and J. Snell. (1992) "Predicting a Change in Taste: Do People Know What They Will Like?" *Journal of Behavioral Decision Making*, 5 (3), 187–200

Kahneman, D., and A. Tversky. (1979) "Prospect Theory: An Analysis of Decision Under Risk." *Econometrica*, 47 (March), 263–291.

———. (1982) "The Psychology of Preferences." *Scientific American*, 246 (1), 160–173.

Kahneman, D.R., and A. Tversky. (eds.) (1982) *"The Simulation Heuristic."* *Judgments under Uncertainty: Heuristics and Biases.* New York: Cambridge University Press.

———. (eds.). (2000) *Choices, Values, and Frames.* Cambridge: Cambridge University Press.

Karlsson, N. (2003) "Consumer Self-Control Strategies: An Empirical Study of Their Structure and Determinants." *Journal of Consumer Policy*, 26 (March), 23–41.

Klaaren, K.J., S.D. Hodges, et al. (1994) "The Role of Affective Expectations in Subjective Experience and Decision Making." *Social Cognition*, 12 (2): 77–101.

Larsen, J., P.A. McGraw, et al. (2001) "Can People Feel Happy and Sad at the Same Time?" *Journal of Personality and Social Psychology*, 81 (4), 684–696.
Levine, L.J. (1997) "Reconstructing Memory for Emotions." *Journal of Experimental Psychology: Genera*, 126 (2), 165–177.
Levine, L.J., and M.A. Safer. (2002) "Sources of Bias in Memory for Emotions." *Current Directions in Psychological Science*, 11 (5), 169–173.
Liberman, N., and Y. Trope. (1998) "The Role of Feasibility and Desirability Considerations in Near and Distant Future Decisions: A Test of Temporal Construal Theory." *Journal of Personality and Social Psychology*, 75(1), 5–18.
Loewenstein, G. (1987) "Anticipation and the Valuation of Delayed Consumption." *Economic Journal*, 97, 666–684.
———. (1996), "Out of Control: Visceral Influences on Behavior." *Organizational Behavior and Human Decision Processes*, 65 (3), 272-292.
Loewenstein, G., and D. Adler. (1995) "A Bias in the Prediction of Tastes." *Economic Journal*, 105, 929–937.
Loewenstein, G., and S. Frederick. (1997) "Predicting Reactions to Environmental Change." In *Environment, Ethics, and Behavior*, ed. M.H. Bazerman, D.M. Messick, A.E. Tenbrusel, and K.A. Wade-Benzoni, pp. 52–72. San Francisco, CA: Jossey Bass.
Loewenstein, G., D. Nagin, and R. Paternoster. (1997) "The Effect of Sexual Arousal on Expectations of Sexual Forcefulness." *Journal of Research in Crime and Delinquency*, 34 (4), 443–473.
Loewenstein, G., T. O'Donoghue, et al. (2000) Projection Bias in Predicting Future Utility (June 6, 2000). Working paper E00–284, Economics Department, University of California, Berkeley.
Loewenstein, G.F., and D. Prelec. (1993) "Preferences for Sequences of Outcomes." *Psychological Review*, 100 (1), 91–108
Loewenstein, G., and D.A. Schkade. (2000) "Wouldn't It Be Nice? Predicting Future Feelings." In *Hedonic Psychology: Scientific Approaches to Enjoyment, Suffering, and Well-being*, ed. D. Kahneman, pp. 85–105. New York: Russell Sage Foundation Press.
Loomes, G., and R. Sunden. (1982) "Regret Theory: An Alternative Theory of Rational Choice under Uncertainty." *Economic Journal,* 92, 805–824.
Lopes, LL. (1984) "Risk and Distributional Inequality." *Journal of Experimental Psychology: Human Perception and Performance*, 10 (4), 465–485.
———. (1987) "Between Hope and Fear: The Psychology Risk." *Advances in Experimental Social Psychology,* 20, 255–295.
———. (1990), "Re-modeling Risk Aversion: A Comparison of Bernoullian and Rank Dependent Value Approaches." *Acting Under Uncertainty: Multidisciplinary Conceptions*, ed. G. M. von Fursetnberg, pp. 267–299. Boston: Kluwer.
Luce, M.F., J.W. Payne, and J. Bettman. (1999) "Emotional Trade-Off Difficulty and Choice." *Journal of Marketing Research*, 36 (May), 143–159.
Lyubomirsky, S. (2001) "Why Are Some People Happier Than Others? The Role of Cognitive and Motivational Processes in Well-being." *American Psychologist*, 56 (3), 239–249.
Lyubomirsky, S., and K.L. Tucker. (1998) "Implications of Individual Differences in Subjective Happiness for Perceiving, Interpreting, and Thinking About Life Events." *Motivation and Emotion*, 22 (2), 155–186.
MacInnis, D. J. (1987) "Constructs and Measures of Individual Differences in Imagery Processing: A Review." In *Advances in Consumer Research*, ed., P. Anderson and M. Wallendorf*,* Vol. 14, 88–92. Provo, UT: Association for Consumer Research.
MacInnis, D.J., and L.L. Price. (1987) "The Role of Imagery in Information Processing: Review and Extensions." *Journal of Consumer Research*, 13 (March), 473–492.
Markus, H., and P. Nurius. (1986) "Possible Selves." *American Psychologist*, 41 (9), 954–969.
Markus, H., and A. Ruvolo. (1989) "Possible Selves: Personalized Representations of Goals." In *Goal Concepts in Personality and Social Psychology*, ed. L. A. Pervin, 211-241. Hillsdale, NJ: Lawrence Erlbaum.
Matlin, M., and D. Stang. (1978) *The Pollyanna Principle.* Cambridge: Schenkman.
McFarland, C., M. Ross, and N. DeCourville. (1989) "Women's Theories of Menstruation and Biases in Recall of Menstrual Symptoms." *Journal of Personality and Social Psychology*, 57 (3), 522–531.
Mellers, B.A. (2000) "Choice and the Relative Pleasure of Consumption." *Psychological Bulletin*, 126 (6), 910–924.

Mellers, B.A., and P.A. McGraw. (2001) "Anticipated Emotions as Guides to Choice." *Current Directions in Psychological Science*, 10 (6), 210–214.

Mellers, B., A. Schwartz, and I. Ritov. (1999) "Emotion-Based Choice." *Journal of Experimental Psychology: General*, 128 (3), 332–345.

Meloy, M.G. (2000) "Mood-Driven Distortion of Product Information." *Journal of Consumer Research*, 27 (3), 345–359.

Metcalfe, J., and W. Mischel. (1999) "A Hot/Cool-System Analysis of Delay of Gratification: Dynamics of Willpower." *Psychological Review*, 106 (1), 3–19.

Mitchell, Terence R., Leigh Thompson, Erika Peterson, and Randy Cronk. (1997) "Temporal Adjustments in the Evaluation of Events: The "Rosy View." *Journal of Experimental Social Psychology*, 33(July), 421–448.

Morwitz, V.G., and G.J. Fitzsimons. (2004) "The Mere Measurement Effect: Why Does Measuring Intentions Change Actual Behavior?" *Journal of Consumer Psychology,* 14(1 and 2), 64–74.

Nelson, P. (1970) "Information and Consumer Behavior," *Journal of Political Economy,* 78 (March–April), 311–329.

Nisbett, R., and L. Ross. (1980) *Human Inference: Strategies and Shortcomings of Social Judgment.* Englewood Cliffs, NJ: Prentice-Hall.

Nunes, J.C. (2000) "A Cognitive Model of People's Usage Estimations." *Journal of Marketing Research*, 37 (4), 397–426.

Nurmi, J.E. (1991) "How Do Adolescents See Their Future? A Review of the Development of Future Orientation and Planning." *Developmental Review*, 11, 1–59.

Nygren, T.E., A.M. Isen, et al. (1996) "The Influence of Positive Affect on the Decision Rule in Risk Situations: Focus on Outcome (and Especially Avoidance of Loss) Rather Than Probability." *Organizational Behavior and Human Decision Processes*, 66 (1), 59–72.

Park, C.W., and S.M. Young. (1986) "The Impact of Involvement and the Role of Commercial Music on Brand Attitude Formation." *Journal of Marketing Research*, 23 (February), 11–24.

Park, C.W., D.L. Mothersbaugh, and L. Feick. (1994) "Consumer Knowledge Assessment." *Journal of Consumer Research*, 21 (June), 71–82.

Patrick, V.M. (2003) What We Will Feel Depends on Who We Are: Cross-Cultural Differences in Affective Forecasting of "Ego-Focused" Versus "Other-Focused" Emotions. Working paper: University of Georgia.

Patrick, V.M., A. Fedorikhin, and D.J. MacInnis. (2004) "The Future Is Colored Red or Black: The Effect of Mood on Affective Forecasting." Working paper, University of Georgia.

Patrick, V.M., and D.J. MacInnis. (2002) "How Will I Feel About It? Affective Misforecasting in Consumer Behavior." In *Advances in Consumer Research,* vol. 29, ed. S. Broniarczyk and K. Nakamoto, pp. 270–276. Atlanta, GA: Association for Consumer Research.

Patrick, V.M., D.J. MacInnis, and C.W. Park. (2004) How Will I Feel about it?: The Asymmetric Impact of Affective Misforecasting on Consumer Satisfaction. Working paper, University of Georgia.

Patrick, Vanessa, Deborah J. MacInnis, and Shashi Matta. (2004) Exploring Shame and Guilt in Consumer Behavior. Working paper, University of Georgia

Perloff, L.S. (1987) *Social Comparison and Illusion of Invulnerability to Negative Life Events. Coping with Negative Life Events: Clinical and Psychological Perspectives.* New York: Plenum.

Perugini, M., and R.P. Bagozzi. (2001) "The Role of Desires and Anticipated Emotions in Goal-Directed Behaviors: Broadening and Deepening the Theory of Planned Behavior." *British Journal of Social Psychology*, 40 (1), 79–98.

Pham, M.T. (1998) "Representativeness, Relevance, and the Use of Feelings in Decision Making." *Journal of Consumer Research*, 25(September), 144–159.

Pham, M.T., T. Meyvis, and N. Zhou. (2001) "Beyond the Obvious: Chronic Vividness of Imagery and the Use of Information in Decision Making." *Organizational Behavior and Human Decision Processes*, 84 (2), 226–253.

Phillips, D.M. (1996) "Anticipating the Future: The Role of Consumption Visions in Consumer Behavior." In *Advances in Consumer Research*, ed. K. Corfman and J. Lynch, vol. 23, pp. 70–75. Provo, UT: Association for Consumer Research.

Phillips, D.M., and H. Baumgartner. (2002) "The Role of Consumption Emotions in the Satisfaction Response." *Journal of Consumer Psychology*, 12 (3), 243–252.

Phillips, Diane M., Jerry C. Olson, and Hans Baumgartner. (1995) "Consumption Visions in Consumer

Decision Making." In *Advances in Consumer Research,* Vol. 22, ed. Frank Kardes and Mita Sujan, pp. 280–84. Provo, UT: Association for Consumer Research.

Raghunathan, R., and K.P. Corfman. (2004) "Sadness as Pleasure Seeking Prime and Anxiety as Attentiveness Prime: The 'Different Affect Different Effect' (Dade) Model." *Motivation and Emotion,* 28 (1), 43–63.

Raghunathan, R., and J. Irwin. (2001) "Walking the Hedonic Product Treadmill: Default Contrast and Mood-Based Assimilation in Judgments of Predicted Happiness with a Target Product." *Journal of Consumer Research*, 28 (December), 355–368.

Raghunathan, R., and Y. Trope. (2002) "Walking the Tightrope Between Feeling Good and Being Accurate: Mood as a Resource in Processing Persuasive Messages." *Journal of Personality and Social Psychology,* 83 (3), 510–525.

Ratner, R.K. and B.E. Kahn. (1999) "Choosing Less-Preferred Experiences for the Sake of Variety." *Journal of Consumer Research,* 26(June), 1–15.

Read, D., and B.V. Leeuwen. (1998) "Predicting Hunger: The Effects of Appetite and Delay on Choice." *Organizational Behavior and Human Decision Processes*, 76 (2), 189–205.

Read, D., G. Loewenstein, et al. (1999) "Choice Bracketing." *Journal of Risk and Uncertainty*, 19 (1–3), 171–197.

Read, D., and G. Loewenstein. (1995) "Diversification Bias: Explaining the Discrepancy in Variety Seeking Between Combined and Separated Choices." *Journal of Experimental Psychology: Applied*, 1(March), 34-49.

Rhodewalt, F., C. Morf, S. Hazlett, and M. Fairfield. (1991) "Self-Handicapping: The Role of Discounting and Augmentation in the Preservation of Self-Esteem." *Journal of Personality and Social Psychology*, 61:, 122–131.

Richard, R., J. van der Plight, and N. de Vries. (1996) "Anticipated Affect and Behavioral Choice." *Basic and Applied Psychology*, 18 (2), 111–129.

Ritov, I., and J. Baron. (1990) "Reluctance to Vaccinate: Omission Bias and Ambiguity." *Journal of Behavioral Decision Making*, 3 (4), 263–278.

Robinson, M.D., and G.L. Clore. (2001) "Simulation, Scenarios, and Emotional Appraisal: Testing the Convergence of Real and Imagined Reactions to Emotional Stimuli." *Personality and Social Psychology Bulletin*, 27 (1), 1520–1532.

Schkade, D.A., and D. Kahneman. (1998) "Does Living in California Make People Happy? A Focusing Illusion in Judgments of Life Satisfaction." *Psychological Science*, 9 (5), 340–346.

Schwartz, N. (1990) "Feelings as Information: Informational and Motivational Functions of Affective States." In *Handbook of Motivation and Cognition: Foundations of Social Behavior*, vol. 2, ed. R. M. Sorrentino, pp. 527–561.. New York: Guilford Press.

Sherman, S.J. (1980) "On the Self-Erasing Nature of Prediction." *Journal of Personality and Social Psychology*, 39(2), 211–221.

Sherman, Steven J., Kim S. Zehner, James Johnson, and Edward R. Hirt. (1983) "Social Explanation: The Role of Timing, Set and Recall on Subjective Likelihood Estimates." *Journal of Personality and Social Psychology*, 44 (6), 1127–1143.

Shiv, B., and J. Huber. (2000) "The Impact of Anticipating Satisfaction on Consumer Choice." *Journal of Consumer Research*, 27 (September), 202–216.

Simonson, I. (1992) "The Influence of Anticipating Regret and Responsibility on Purchase Decisions." *Journal of Consumer Research*, 19 (1), 105–118.

Snell, Jackie, and Brian J. Gibbs. (1995) "Do Consumers Know What They Will Like?" In *Advances in Consumer Research*, vol. 22, ed. F. Kardes and M. Sujan, pp. 277–279.

Snell, J., B.J. Gibbs, and C. Varey. (1995) "Intuitive Hedonics: Consumer Beliefs about the Dynamics of Liking." *Journal of Consumer Psychology*, 4(1), 33–60.

Snyder, C.R. (2000) "The Past and Possible Futures of Hope." *Journal of Social and Clinical Psychology*, 19 (1), 11–28.

Stayman, D., M. Dana, et al. (1992) "Some Effects of Schematic Processing on Consumer Expectations and Disconfirmation Judgments." *Journal of Consumer Research*, 19 (September), 240–255.

Strathman, A., F. Gleicher, D.S. Boninger, and C.S. Edwards. (1994) "The Consideration of Future Consequences: Weighing Immediate and Distant Outcomes of Behavior." *Journal of Personality and Social Psychology*, 66 (4), 742–752.

Suh, E., E. Diener, and F. Fujita. (1996) "Events and Subjective Well-being: Only Recent Events Matter." *Journal of Personality and Social Psychology,* 70 (5), 1091–1102.

Taylor, S.E., and J.D. Brown. (1988) "Illusion and Well-Being: A Social Psychological Perspective on Mental Health." *Psychological Bulletin*, 103 (2), 193–210.
Taylor, S.E., M. Kemeny, et al. (2000) "Psychological Resources, Positive Illusions and Health." *American Psychologist*, 55 (1), 99–109.
Taylor, S.E., L. Pham, I.D. Rivkin, and D.A. Armor. (1998) "Harnessing the Imagination: Mental Stimulation, Self-regulation, and Coping." *American Psychologist*, 53 (4), 429–439.
Tice, D.M., and R.F. Baumeister. (1984) Self-Handicapping, Self-Esteem, and Self-Presentation. Paper presented at the meeting of the Midwestern Psychological Association, Chicago.
Trommsdorff, G. (1983) "Future Orientation and Socialization." *International Journal of Psychology*, 18 (5), 381–406.
Trope, Y., and N. Liberman. (2000) "Temporal Construal and Time-Dependent Changes in Preference." *Journal of Personality and Social Psychology*, 79 (6), 876–889.
Trope, Y., and N. Liberman. (2003), "Temporal Construal," *Psychological Review,* 110 (3), 403–421.
Vallone, R.P., D.W. Griffin, et al. (1990) "Overconfident Prediction of Future Actions and Outcomes by Self and Others." *Journal of Personality and Social Psychology*, 58 (4), 582–592.
Weinstein, N.D. (1980) "Unrealistic Optimism About Future Life Events." *Journal of Personality and Social Psychology*, 39, 806–820.
Wilson, T.D., and D.T. Gilbert. (2003) "Affective forecasting." In *Advances in Experimental Social Psychology*, ed. M. Zanna, Vol. 35, pp. 345-411. New York: Elsevier.
Wilson, T.D., D.T. Gilbert, and D.B. Centerbar. (2002) "Making Sense: The Causes of Emotional Evanescence." In *Economics and Psychology,* ed. J. Carillo and I. Brocas, pp. 209–233. Oxford: Oxford University Press.
Wilson, T.D., D.T. Gilbert, and T. Salthouse. (2001). *Predicted emotional reactions across the adult life span.* Unpublished raw data. University of Virginia.
Wilson, T. D., J. Meyers, et al. (2001) "Lessons from the Past: Do People Learn from Experience that Emotional Reactions Are Short-Lived?" *Personality and Social Psychology Bulletin*, 27 (12), 1648–1661.
Wilson, T.D., T.P. Wheatley, J.M. Meyers, D.T. Gilbert, and D. Axsom. (2000) "Focalism: A Source of Durability Bias in Affective Forecasting." *Journal of Personality and Social Psychology,* 78 (5), 821–836.
Woodzicka, J.A., and M.LaFrance. (2001) "Real Versus Imagined Gender Harassment." *Journal of Social Issues,* 57, 15–30.
Zeelenberg, M., J. Beattie, J. van der Plight, and N.K. de Vries. (1996) "Consequences of Regret Aversion: Effects of Expected Feedback on Risky Decision Making." *Organizational Behavior and Human Decision Processes,* 65 (2), 148–158.

CHAPTER 3

# CONSUMER USE OF THE INTERNET IN SEARCH FOR AUTOMOBILES

## Literature Review, a Conceptual Framework, and an Empirical Investigation

BRIAN T. RATCHFORD, MYUNG-SOO LEE, AND DEBABRATA TALUKDAR

**Abstract**

*We review the literature related to use of the Internet as a vehicle for information search, and we make suggestions for additional work in this area. Using detailed data on types of Internet sources used by automobile buyers from a survey of consumers who bought automobiles in the summer of 2001, we also study the determinants of the choice of different types of Internet sources and the substitution patterns between those types and other non-Internet sources. For this purpose we develop and test a general model of the choice of information sources.*

The advent of the Internet created a new vehicle for consumers to access information on automobiles, other durable goods, and virtually everything else. The use of the Internet as an information source for automobiles has grown rapidly and now stands at about 60% of buyers of new cars who use the Internet in their search (J.D. Power and Associates, 2002). As one might expect given the addition of a new information source, efforts have been made to study the impact of the Internet on automobile buying. Studies by Scott Morton, Zettelmeyer, and Silva-Risso (2001, 2003, 2004), Klein and Ford (2003), and Ratchford, Lee, and Talukdar (2003) have examined various aspects of the Internet's impact on automobile buying. Scott Morton et al. document that the use of the Autobytel.com referral service leads to lower prices for consumers and appears to most benefit consumers who would do poorly in traditional price negotiations. Klein and Ford (2003) study the search behavior of samples of car buyers and car shoppers who selected the Internet as an information source. Ratchford, Lee, and Talukdar (2003) model the impact of the Internet on the use of alternative sources and on total search effort.

In evaluating how the Internet substitutes for conventional sources, Ratchford, Lee, and Talukdar (2003) found that they could not reject the proportional draw hypothesis that the Internet substitutes in a constant proportion to the pre-Internet use of each source. However, their data on Internet use was somewhat lacking in detail, possibly masking more complex substitution patterns between the Internet and conventional sources. In general, aside from Klein and Ford (2003), there is not much evidence on exactly what types of information about automobiles is obtained from the Internet and on how the Internet is employed in search for automobiles.

In this chapter we review the literature on the choice of information sources in general, and on the use of the Internet as an information source in particular. We also present the results of an empirical study that seeks to determine the extent of use of different Internet sources of information in search for automobiles, the perceived value of such sources of Internet information, and the variation of these variables across car buyers. We also examine substitution between the Internet and conventional sources. In particular, we seek to determine whether the proportional draw model in Ratchford, Lee, and Talukdar (2003) holds up when more detailed information on Internet use is employed. To study the usage and value of different Internet sources, we use a survey of recent car buyers who purchased their autos in summer 2001, which includes detailed questions on the use of information sources in general and the Internet specifically. To study the substitution of the Internet for other sources, we employ data on the choice of conventional sources in 1989 to obtain a baseline prediction of how consumers with a given set of characteristics would have employed sources in 2001. We then use the 2001 data on Internet use to determine systematic deviations form this baseline.

## Literature Review

Although our objective is to study the impact of the Internet on the use of other information sources in the context of automobile purchases, we need to make some observations on what is known about the use of information sources in general. Accordingly, we will begin by reviewing studies of consumer use of information sources. After that we will discuss what is known about the Internet as an information source. Finally, we will discuss applications of these two strands of literature to the specific context of Internet use in automobile purchases.

### *Information Sources*

There is a large literature on consumer search that dates to the 1950s (see Beatty and Smith, 1987 for an excellent review of the earlier literature). Although most of these studies consider the determinants of total search effort rather than use of individual sources (e.g., Punj and Staelin, 1983; Beatty and Smith, 1987; Srinivasan and Ratchford, 1991; Moorthy, Ratchford, and Talukdar, 1997), there is also a literature on the allocation of the effort among information sources. Perhaps the most notable examples of these studies of the use of information sources are Claxton, Fry, and Portis (1974), Westbrook and Fornell (1979), Kiel and Layton (1981), Furse, Punj, and Stewart (1984), and Wilkie and Dickson (1985). These studies are primarily attempts to identify typologies of information source use through surveys of recent buyers. Employing factor analysis and cluster analysis of survey data, Kiel and Layton (1981), and Furse, Punj, and Stewart (1984) develop a typology of source use for automobiles that finds clusters of consumers with different patterns; Klein and Ford (2003) replicate this approach for their sample of Internet users.

These studies on the use of information sources, and on studies of search in general, all show that a large segment of consumers does not search much at all. For example, Wilkie and Dickson (1985) found that 32% of a sample of major household appliance buyers considered only one brand and that 45% spent less than two hours in shopping for an appliance. Lapersonne, Laurent, and Le Goff (1995) found that 22% of a sample of car buyers in France considered only one brand

and 17% of these considered only the brand owned previously.

The studies of information source use discussed above are primarily empirical and do not offer a well-developed theory of the choice of sources. Although there are many theoretical models of total search (Punj and Staelin, 1983; Srinivasan and Ratchford, 1991; Ratchford and Srinivasan, 1993; Schmidt and Spreng, 1996; Moorthy, Ratchford, and Talukdar, 1997), less work has been done on the use of specific information sources. However there has been work on modeling the choice of sources and on modeling types of sources and their relationship to the information needs of buyers. With respect to choice of sources, Ratchford (1982) proposed that each source would be used to the point where its marginal benefit equals its marginal cost, which provides the starting point for the model considered in this paper. Extending this general benefit-cost framework, Hauser, Urban, and Weinberg (1993) develop and estimate a model of the sequence of choice of sources. Their model is based on consumers choosing a source that gives the highest expected benefit relative to time cost at each stage in the search process. The model allows for a detailed updating of expected utility of each alternative based on the information obtained at each stage. These updated utilities in turn provide the basis for the benefit-cost estimates at the next stage of the search. This model was applied with good results in the context of a laboratory simulation of the information search process.

Perhaps the most complete survey studies of the choice of information sources are Strebel, Erdem, and Swait (2004), and Erdem, Keane, and Strebel (2004). Both studies use the same data set, which is a panel where data on choice of sources and type of PC were collected in six waves. At each wave, data were compiled on the use of each of five information sources during the time interval since the preceding wave, on quality perceptions of competing PC types, and on price expectations. Erdem, Keane, and Strebel's research (2004) is especially noteworthy because this work develops a complete structural model of both the choice of sources and final choice of PC type. This model incorporates price expectations, perceived quality, quality uncertainty, learning, and heterogeneity, making it a completely integrated theoretical and empirical model of the use of information sources. If panel data can be obtained, which is difficult, the approach employed in Erdem, Keane, and Strebel (2004) should be applicable in other search contexts. The panel data have the advantage of tracing search behavior as it unfolds, which cannot be done if the usual retrospective survey data are employed.

With respect to developing typologies of types of sources, research has traditionally been classified along two dimensions (Klein and Ford, 2003): seller dominated–independent, personal–interpersonal. For example, Beatty and Smith (1987) classify sources as retail (seller–personal), media (seller–impersonal), interpersonal (independent–personal), and neutral (independent–impersonal). As discussed later in this chapter, Klein and Ford (2003) add a third dimension, online–offline. While there has not been much work to predict how consumers will use these sources, Ratchford, Talukdar, and Lee (2001) model the benefits of sources as related to three types of attributes: functional (related to how something works, such as gas mileage or acceleration), expressive (use of the product for self-expression, such as style or sporty), and price. Klein and Ford (2003) present an alternative model in which the benefits of sources vary with remote search attributes (information can be obtained from inspection), in-person search attributes (they require direct inspection), and experience attributes (they can only be verified postpurchase).

In sum, much less research has been done on the choice of information sources than on search in general. A common finding of both the literature on the choice of sources and of the broader literature on search has been that a substantial proportion of consumers make little or no use of any source. The idea underlying the model in this chapter—that sources are combined in a way that produces information most cost-effectively—dates back at least to Ratchford (1982), and has been developed more fully by Hauser, Urban, and Weinberg (1993) and Erdem, Keane, and Strebel (2004). While typologies of types of information sources exist, and there are some theories about the information types that consumers will use them for, more work at developing the link between types of information sought and the choice of sources would be useful.

### *Internet as an Information Source*

The early literature on the Internet, which is still only about seven years old, speculated on the impact of this medium on various markets. The pioneering article of Alba et al. (1997) discusses the potential impact of electronic commerce on consumers, retailers, and manufacturers. However, this article does not contain a formal model of the choice of the Internet as an information source. Bakos (1997) does present a formal search model that considers the impact of the Internet on equilibrium outcomes. However, the basic focus of the Bakos paper is on market outcomes, not individual differences in search or choice of different sources. The basic point of his paper is that the Internet will lead to considerable gains in market efficiency because it will greatly lower search costs.

It was not long until scholars began to uncover exceptions to this point. Lal and Sarvary (1999) point out that, in cases where information about alternatives is best acquired by inspection at retail, the option of purchasing online creates a disincentive to spend extra time going to a retailer. This makes it less likely that the consumer will examine alternatives, which makes the consumer less informed and actually lessens competition. In fact, the seller can capture the consumer's saving in transportation costs through higher Internet prices. Lynch and Ariely (2000) show that information provided on the Internet may actually decrease price sensitivity, thereby limiting price competition. The authors demonstrate experimentally that wine shoppers become more price-sensitive when different Web sites carry the same wine, while they become less price-sensitive when different sites carry unique wine.

There is also considerable evidence that Internet markets do not function as smoothly as predicted by Bakos (1997). Many studies have documented substantial price dispersion in Internet markets, even among items displayed in shop-bots where price comparison across sellers should be virtually costless (see the review by Pan, Ratchford, and Shankar, 2004).[1] This price dispersion has persisted as Internet markets have matured and cannot readily be explained by differences in services across Internet retailers (Pan, Ratchford, and Shankar, 2002). Baye and Morgan (2001) argue that the ex ante price dispersion results because fees charged by owners of shop-bots serve to limit price competition. Ellison and Ellison (2004) argue that online sellers have an incentive to create search costs by obfuscating their true prices through devices such as adding on shipping fees and that these seller-created costs lead to price dispersion.

Click-stream data have been used to develop typologies of Internet search behavior and to model conversion from search to purchase (Moe and Fader, 2001, 2004; Bucklin and Sismeiro, 2003). Using click-stream data, Johnson et al. (2004) show that, contrary to what one would expect from costless search, consumers typically visit only a small proportion of the available book, CD, or travel sites. Thus, the finding of limited search in other venues appears to extend to the Internet.

Despite the evidence that Internet markets may not function as well as initially expected, there is evidence that the Internet has led to lower prices in some markets. Brown and Goolsbee (2002) show that a substantial reduction in term life insurance prices is attributable to the introduction of Internet sites for searching for this insurance. In a series of studies, Scott Morton, Zettelmeyer, and Silva-Risso (2001, 2003, 2004) have shown that Internet car referral services, and Internet use in general, are associated with lower car prices. In particular, those with high search costs, such as women and minorities, who take advantage of buying services, receive lower prices than they would obtain without these services. The Scott Morton et al. studies will be discussed in more detail later in this chapter.

### *Internet and Automobile Purchases*

Few academic studies have been published on the impact of the Internet on the use of other information sources, and empirical studies of how consumers employ the Internet in relation to other sources in their search effort appear to be confined to the domain of automobiles. Ratchford, Talukdar, and Lee (2001) present a general model of the choice of the Internet and other information sources. In this model, the use of specific types of sources depends on types of attributes that are salient, prior information, skill at using each source, ease of accessing a source, and income. On the basis of this model, a number of general propositions about the use of the Internet have been developed.

Ratchford, Lee, and Talukdar (2003) present an extension of their 2001 model to the specific case of search for automobiles and provide specific functional forms for prior information and the productivity of sources that can be parameterized. The resulting model of the choice of sources is estimated in their 2003 paper. Their key findings are that the Internet appears to reduce the share of effort devoted to other sources by approximately the same proportion and that the Internet generally leads to a reduction in total search. A limitation of their study is that it only considers overall Internet use, and not the use of specific Internet sources.

Several other recent papers consider the use of the Internet in search for automobiles and present results that are complementary to those presented in this study. Klein and Ford (2003) collected survey data using the Internet on search for automobiles from 369 respondents who were either recent buyers or current shoppers. A key finding of their study is that online use appears to have three dimensions: (1) manufacturer/dealer sources, (2) buying services and other third parties, and (3) bulletin board/chat sources. These dimensions each have offline counterparts: (1) dealer visits/advertisements, (2) *Consumer Reports* and other third-party sources of print information, and (3) interpersonal contact with friends/relatives. Since the data for the Klein and Ford (2003) study were gathered on the Internet, a drawback of their study is that it does not contain information about the information source use of car buyers who do not use the Internet.

As noted above, Scott Morton, Zettelmeyer, and Silva-Risso (2001, 2003, 2004) have studied the impact of the Internet on automobile prices. The first two papers examined the effect of Internet referral services on automobile dealer pricing in California using actual transaction data. These studies indicate that an average customer of Autobytel.com does, in fact, pay less for a given car than a customer who does not use this referral service. This is evidence that Internet use, or at least the use of Internet referral services, leads to better buys for automobiles.

Using a unique database linking data on transactions and survey responses from the same respondents, Scott Morton, Zettelmeyer, and Silva-Risso (2004) provide evidence that the Internet leads to lower prices by providing information on dealer costs and by providing access to online buying services. The buying services are effective because of the clout they have over participating dealers: the dealers do not want to lose the source of added revenues that the services provide. The role of the Internet is to make the buying services readily accessible to consumers. Aside from showing the impact of buying services, the authors also find that Internet price information is only beneficial to those with a high disutility of bargaining.

### *Summary*

The existing evidence indicates that the Internet in general provides information that parallels the information provided by other sources and that it substitutes for the other sources. However whether this result holds for specific types of Internet sources, such as manufacturer Web sites, third-party Web sites, or bulletin board/chat sites, is unclear. One objective of this study is to provide an answer to this question in the case of search for automobiles. While the Internet appears to fall short of providing frictionless markets, the available evidence indicates that the Internet does provide benefits in terms of reduced search effort and lower prices. Whether the Internet also leads consumers to make better decisions on attributes other than price is less clear, and little is known about the impact of specific Internet sources other than automobile buying services on prices and brand choice. An objective of our empirical study is to shed light on these issues. Specifically, we attempt to determine the relative value of different Internet sources for automobile purchases by examining relationships between consumer self-reports of different types of information obtained from the Internet and the use of different Internet sources.

## Theoretical Framework

We wish to develop a theoretical framework that will explain a consumer's choice of information sources and total amount of search. This model should be capable of explaining the effect of the Internet on other sources and should be useful as an organizing framework for the analysis of our survey data. To this end, a consumer's process of information search and acquisition can be thought of as a production process in which the consumer seeks to maximize the difference between the utility gain and cost of search (Ratchford 1982; Hauser, Urban, and Weinberg, 1993). Information sources can usefully be identified as inputs to this production process in which time spent with each source leads to increased information, and ultimately a better decision (Ratchford, 1982). One source of information is memory or prior knowledge. In this study, we focus on the choice of external sources of information given a level of information that the consumer has in memory prior to the commencement of search.

We begin with the model developed in Ratchford, Lee, and Talukdar (2003), which is a general model of the consumer's choice of information sources, and of the decision to allocate a total amount of time across sources. This model is as follows. Given her opportunity cost of time, the consumer decides how much time to spend on searching each information source to maximize the net benefit of search. Specifically, let $g$ be the difference between the consumer's expected utility of a choice in the focal product class under complete information and the consumer's expected utility under no information (random choice). Let $I$ be a measure of the worth of the consumer's stock of information, which varies between $I = 0$ (if the consumer has no information) and $I = 1$ (if the consumer has complete information). A priori the consumer's gain from information is then $gI$, which = 0 if $I = 0$ and the consumer makes a random choice, and equals $g$ if $I = 1$ and the consumer makes a fully informed choice.

The consumer's stock of information can be expressed as $S + F$, where $S$ is prior information and where $F$ is the amount of information added to the stock between the time the search commences and the purchase is made. There must be diminishing returns to information; for example, the function relating $I$ to $S + F$ must exhibit diminishing returns. A function that exhibits diminishing returns, that fits the requirement that $I$ be bounded between 0 and 1, and that makes it possible to obtain closed-form solutions to observable variables is $I = 1 – e^{-(S+F)}$. The information produced in the search, $F$, is produced by allocating $t_1, \dots, t_n$ units of time to $n$ different sources:

$F = F(t_1, \ldots, t_n; H)$, where $H$ is a vector of consumer characteristics that affects the productivity of each source. If corner solutions in which all available time is allocated to one source are to be avoided, there must be diminishing returns to time spent with a given source.

In modeling the consumer's costs of search, we ignore for simplicity the out-of-pocket costs associated with the use of information sources, such as the money needed to buy *Consumer Reports*, which are usually incidental.[2] On the other hand, the time required to acquire and process the information from each source cannot be devoted to other activities, and therefore has an opportunity cost that cannot be ignored. We assume that each unit of time devoted to a given information source costs $w(H)$, which is constant across sources. Consequently, the consumer's cost of search is $C = w(\sum_j t_j)$. There may also be certain cognitive costs or benefits associated with the time devoted to the search. These are best modeled as affecting $w$, the cost of a unit of time (Marmorstein, Grewal, and Fishe 1992). For example, negative emotions associated with buying a car (Bettman, Luce, and Payne 1998) may make spending time in the search distasteful, thereby increasing $w$; conversely, enjoyment of shopping for cars would decrease $w$ (Marmorstein, Grewal, and Fishe 1992).[3]

The above discussion leads to a definition of the consumer's maximization problem:

$$(1) \qquad MaxB = gI - w\left(\sum_j t_j\right) = g\left(1 - e^{-(S+F)}\right) - w\left(\sum_j t_j\right).$$

Taking first-order conditions, we get relationships of the form:

$$(2) \qquad \frac{\partial B}{\partial t_i} = g\left(e^{-(S+F)}\right)\frac{\partial F}{t_i} = w \qquad \textit{for all } \mathrm{i}.$$

Equation 2 equates the marginal gain to information from each source with their common marginal cost.[4] Equation 2 implies that for all sources getting a positive allocation of time:

$$(3) \qquad \frac{\partial F}{\partial t_1} = \frac{\partial F}{\partial t_2} = \ldots = \frac{\partial F}{\partial t_n} = \frac{w}{g} e^{S+F},$$

where the term on the right can be interpreted as the marginal cost per unit of information, which increases as the consumer becomes more informed.[5] The expressions on the left indicate that the marginal gain in information from each source that is used must be equal. If $F$ is parameterized, Equation 3 can be used to develop expressions for the relative usage of each source.

Ratchford, Lee, and Talukdar (2003) modeled $F$ as a log-linear function of time with each source: $F = \sum a_i \ln t_i$. This leads to closed-form expressions for total search time and share of time with each source. However, as shown below, this model leads to a potentially restrictive substitution pattern that we wish to test empirically.

The point of departure of the present paper is to represent $F$ with the translog form, which is a flexible second-order approximation to any general functional form that is often used in the analysis of cost and production functions:

$$(4) \qquad F = \sum a_i \ln t_i + (1/2)\sum\sum b_{ij} \ln t_i \ln t_j.$$

The coefficients $b_{ij}$, which are assumed to be symmetric ($b_{ij} = b_{ji}$), identify substitution patterns. If $b_{ij} > 0$, the marginal effect of $t_i$ on $F$ increases with $t_j$; if $b_{ij} < 0$, the marginal effect of $t_i$ on $F$ decreases with $t_j$, and if $b_{ij} = 0$, the marginal effect of $t_i$ is unaffected by $t_j$. Differentiating $F$ with respect to each of the $t_i$ as in Equation 3, setting the results equal to one another, and performing some algebraic manipulations lead to the following expression for the share of time devoted to the use of any source $k$:

$$s_k = \frac{t_k}{\sum_i t_i} = \frac{a_k + \sum_j b_{kj} \ln t_j}{\sum_i a_i + \sum_i \sum_j b_{ij} \ln t_j}. \tag{5}$$

If all of the second-order effects $b_{ij} = 0$, $s_k$ reduces to a simple linear function of the $a$ parameters that exhibits the iia and proportional draw properties. When all $b_{ij} = 0$, Equation 5 leads to a simple closed-form solution for time allocated to each source that cannot readily be obtained from the general case expressed in Equation 5 (Ratchford, Lee, and Talukdar, 2003).

To be more precise about iia and proportional draw, suppose that all of the $b_{ij} = 0$ in Equation 5. Then $s_k = a_k/\sum a_i$. Introduce a new alternative such as the Internet. Then $s'_k = a_k/(\sum a_i + a_I)$, where $I$ refers to Internet. To demonstrate iia, it is easily seen that $s'_{k+}/s'_j = a_k/a_j = s_k/s_j$. That is, the share of $k$ relative to $j$ is unaffected by the presence of a new source since the denominator terms cancel in computing relative shares. To demonstrate proportional draw, we see that $s'_k/s_k = \sum a_i/(\sum a_i + a_I)$, for all $k$. That is, the introduction of the new alternative reduces the shares of all of the existing alternatives in the same proportion.[6]

Since we have data on a cross section of consumers, we need to consider the variation in Equation 5 across consumers, $h$. This can be expressed as:

$$s_{kh} = \frac{t_{kh}}{\sum_i t_{ih}} = \frac{a_{kh} + \sum_j b_{kjh} \ln t_{jh}}{\sum_i a_{ih} + \sum_i \sum_j b_{ijh} \ln t_{jh}} = f(\mathrm{H}) + \varepsilon, \tag{6}$$

where **H** is a vector of consumer characteristics that affect the parameters of the function relating search time to its outcomes and $\varepsilon$ . Given that our cross-sectional data contains only one observation per person, and there is likely to be considerable heterogeneity in the various parameters, these are hard to identify. However, we can identify relationships between shares and household characteristics that have a plausible explanation. We can use these to predict what shares would be in the absence of the Internet. Systematic deviations from the predicted shares with Internet use will help to uncover the impact of the Internet on the various cross effects.

***Test for Proportional Draw***

As in Ratchford, Lee, and Talukdar (2003), our strategy for examining substitution patterns between the Internet and other sources will be to test the proportional draw hypothesis that the Internet draws search time from other sources in proportion to the pre-Internet use of each source. This hypothesis implies that the Internet substitutes for other sources according to a particular pattern. Deviations from this hypothesis will indicate instances in which other sources are more or less substitutable than this hypothesis implies. Klein and Ford (2003, p. 34) point out that the

Internet has a "remarkable capacity to provide information that more or less corresponds" to information that is provided by other sources, lending credence to the proportional draw hypothesis. Ratchford, Lee, and Talukdar (2003) also found evidence in favor of this hypothesis. We will deepen this analysis by considering more specific Internet and non-Internet sources. If proportional draw is found to be a reasonable approximation, a tractable model of search effort can readily be developed.

To develop the test, let $F$ in Equation 4 express the relationship between time spent with each source and information prior to the Internet, and $F'$ express this relationship after the introduction of the Internet. Then by expanding Equation 4, and if there are $I$ types of Internet sources, $F'$ can be expressed as (subscripts $h$ for consumer are suppressed):

$$F' = F + \sum a_I \ln t_I + (1/2)\sum\sum b_{iI} \ln t_i \ln t_I + (1/2)\sum\sum b_{II} \ln t_I \ln t_I . \quad (7)$$

Then, for any non-Internet source $i$ we have:

$$\frac{\partial F'}{\partial t_i} = \frac{\partial F}{\partial t_i} + \frac{\sum_I b_{iI} \ln t_I}{t_i}. \quad (8)$$

If there is a cross effect between the Internet and source *i,* Internet use will have an impact on its marginal productivity. We wish to examine how the share of the non-Internet sources among themselves (excluding the Internet share from ex-post share calculation) will change after the introduction of the Internet. Denote $s_{k0}$ as pre-Internet share and $s_{kI}$ as post-Internet share of non-Internet source $k$ among the non-Internet sources. Then after applying some algebraic manipulations to the expressions in Equation 8, and using the equalities expressed in Equation 3, we get:

$$s_{k1} = \frac{s_{k0} + \left(\sum_I b_{kI} \ln t_I\right)/D_0}{1 + \left(\sum_I \ln t_I \sum_i b_{iI}\right)/D_0}, \quad (9)$$

where $D_0$ is the denominator of Equation 5. If all $b_{iI} = 0$, the relative shares of the non-Internet sources are unchanged between the two periods. The Internet will draw in the same proportion from each source. Subtracting $s_{k0}$ from $s_{k1}$ leads to the following expression for the impact of the internet on $s_k$:

$$\Delta s_k = s_{k1} - s_{k0} = \frac{\sum_I b_{kI} \ln t_I - \left(\sum_I \ln t_I \sum_i b_{iI}\right) s_{k0}}{D_0 + \left(\sum_I \ln t_I \sum_i b_{iI}\right)}. \quad (10)$$

If all $b_{iI} = 0$, the numerator of Equation 10 is 0, and $\Delta s_k = 0$. Assuming that $\left(\sum_I \ln t_I \sum_i b_{iI}\right)$ is not zero, $\Delta s_k$ in Equation 10 is positive if:

$$\frac{\left(\sum_I b_{kI} \ln t_I\right)}{\left(\sum_I \ln t_I \sum_i b_{iI}\right)} > s_{k0}, \quad (11)$$

for source $k$ relative to other sources, negative if the inequality is reversed, and 0 if Equation 11 is an equality. The expression on the left of Equation 11 can be interpreted as a search time weighted average of the cross effects of the Internet for source $k$ relative to all conventional sources. If these cross effects for source $k$ relative to other sources are larger than $s_{ko}$, its share will increase; if they are smaller than $s_{k0}$, its share will decrease; if they are the same as $s_{ko}$, its share will be unchanged. If there is only one Internet source (e.g., the Internet itself), Equation 11 reduces to $b_{kI}/\sum_i b_{iI}$.

The foregoing discussion suggests a test of the proportional draw hypothesis. We first estimate $s_{kh0} = \frac{t_{kh}}{\sum_i t_{ih}} = f(\mathbf{H}) + \varepsilon$ on base year (1989) data. This gives an estimate of $\hat{f}(\mathbf{H})$. We use this to estimate an expected current-year (2001) share (relative to the original non-Internet sources) for each current respondent: $\hat{s}_{kh0} = \hat{f}(\mathbf{H})$. Under the null hypothesis of proportional draw, the difference between actual and expected share is $\Delta s_{kh} = s_{kh1} - \hat{s}_{kh0} = \hat{\varepsilon}$. Under the alternate hypothesis $\Delta s_{kh} = s_{kh1} - \hat{s}_{kh0} = \hat{\varepsilon} + d(t_I)$, as can be seen from Equation 10. The hypothesis can be tested by regressing $\Delta s_{kh}$ on measures of Internet search time.

*Production of Different Types of Information by Internet Sources*

In our 2002 questionnaire, we have self-report data on amount of different types of information obtained from the Internet on a 6-point scale ranging from "no information" to "a lot of information." In this section, we outline how these data can be incorporated into our theory. If there are $T$ types of information (price information, performance information, etc.), and we assume proportional draw, the definition of $F$ can be stated as $F = \sum_T k_T V_T$, where $V_T = \sum_i b_{iT} \ln(t_i)$. In these expressions, $k$ is an importance weight for information type $T$, $V$ is total amount of information of type $T$, and $b$ relates amount of information of type $T$ to time spent with source $i$. High values of $b$ would indicate that source $i$ is relatively effective at producing information of type $T$. If $k$ for this information type is relatively large, this information type would result in a relatively large improvement in the consumer's decision. Consequently, if both $k$ and $b$ are high, we should expect time spent with source $i$ to be relatively high. Given that our scales measure $V_i$, or how much information of type $i$ was obtained, we can estimate $b_{iT}$ by regressing between $V$ on $\ln(t_i)$. We can relate this source-specific expression for $F$ back to our original function in Equation 4 with the cross-product terms eliminated (that is, under the premise of proportional draw) as:

$$(12) \qquad F = \sum_T k_T \sum_i b_{it} \ln(t_i) = \sum_i \left(\sum_T k_T b_{iT}\right) \ln(t_i) = \sum_i a_i \ln(t_i).$$

Equation 12 indicates that the productivity parameter $a_i$ is determined by a source's ability to produce ($b_{iT}$) important types of information ($k_T$).

## Data

### *Description of Data and Measures*

Data used in this study came from two independent mail surveys conducted in February 1990 and 2002.[7] Data collection in these surveys followed exactly the same procedures to make sure that we have two sets of comparable data. The surveys were sent to lists of 3000 buyers of new cars in the Buffalo, New York area (specifically, ZIP codes with first digits 140, 141, 142) in July and August of the preceding year (1989, 2001). The list, which was supplied by R.L. Polk, was a systematic random sample of these buyers. In addition to the initial survey, there was a follow-up with a reminder card in each case. A total of 843 usable responses were obtained from the February 1990 survey; a total of 705 usable responses were obtained from the February 2002 survey. Because of missing data, the number of cases available for the various analyses varies slightly from these totals.

A problem with the survey, which is shared with virtually all studies of search behavior (Moorthy, Ratchford, and Talukdar, 1997; Strebel, Erdem, and Swait, 2004; and Erdem, Keane, and Strebel, 2004 are exceptions), is that several months elapsed between the purchase and data collection, taxing respondents' ability to recall their search. However, automobiles are a major purchase, making it likely that respondents will be able to recall their behavior. Our results are broadly consistent with previous studies of search for automobiles, indicating that our study does not pose any special problems. Moreover, the impact of forgetting should be the same for both surveys and should therefore cancel out in our analysis. Because of the difficulty of identifying buyers or potential buyers ahead of time, the postpurchase procedure that we employed is the only feasible method for conducting large-scale surveys of search behavior.

### *General Measures of Search*

A list of the general measures of search time employed in the 2002 survey is presented in Table 3.1; except for the Internet, the 1990 survey contained exactly the same measures. The list of 11 search activities is meant to be a comprehensive list of different activities that an individual might engage in. It represents an attempt to refine the similar list presented in Furse, Punj, and Stewart (1984). Adding the self-reported time spent on each activity would provide an estimate of the total resources devoted to the search. To check responses, we estimated total search as the sum of time spent across the 11 sources of information listed in Table 3.1 (10 sources in 1990). This estimate was compared with another survey question that sought a direct estimate of total time.[8] The correlations between the alternative measures across the samples were .88 for the 1989 sample and .83 for the 2001 sample. Thus, the two alternative measures show reasonable agreement.

It was necessary to place our list of time expenditure categories into a broader categorization of types of information sources. Consistent with the prior literature on search behavior, Beatty and Smith (1987) classify conventional sources as media, retail, interpersonal, and neutral. Klein and Ford (2003) suggest that conventional sources can be classified into a 2 x 2 framework, with one dimension being independent–seller dominated, and the other being interpersonal–impersonal. This can be reconciled with Beatty and Smith (1987): media is impersonal–seller dominated, retail is interpersonal–seller dominated, interpersonal in Beatty and Smith (1987) is interpersonal–independent, and neutral in Beatty and Smith (1987) is impersonal–independent in Klein and Ford's (2003) scheme. Klein and Ford (2003) also hypothesize that there is a third dimension, online–offline, in which online sources have counterparts to each of the offline sources. They find support for this hypothesis.

Based on previous literature and the data available for empirical work, we define the following categories of time expenditures on conventional external sources of information for our study:

- *Dealer-related:* time for travel to and from dealer, showroom, salesperson, negotiation, and test drives. This corresponds to Beatty and Smith's retail category and to Klein and Ford's

Table 3.1

**Measures of General Search Included in 1990 and 2002 Surveys**

In deciding which car to buy and which dealer to purchase it from, hours and minutes personally spent on each of the following activities:

- Talking to friends/relatives about new cars or dealers
- Reading books and magazine articles
- Reading advertisements/listening to advertising on TV/Radio
- Reading about car ratings in magazines (e.g., *Consumer Reports*)
- Reading automobile manufacturer ratings/pamphlets
- Searching for information about cars and dealers on the Internet (2000 and 2002 only)
- Driving to and from dealerships
- Looking around the showrooms
- Talking to sales people
- Price negotiation with the dealer
- Test driving cars

interpersonal–seller dominated category. This is the primary source of information on attributes that can only be ascertained by direct inspection (how the car feels in comfort and handling), as well as the place where price negotiation takes place.

- *Advertising:* time spent by the respondent looking at advertisements and brochures. This corresponds to Beatty and Smith's media category and Klein and Ford's impersonal–seller dominated category.
- *Friends/relatives:* time spent by the respondent obtaining information from friends and relatives. This corresponds to Beatty and Smith's interpersonal category and to Klein and Ford's interpersonal–independent category.
- *Nonadvocate:* time spent by the respondent obtaining information from impersonal sources in print media not sponsored by the dealer or manufacturer. Examples are *Consumer Reports* and other ratings or price information not sponsored by the dealer or manufacturer. These correspond to Beatty and Smith's neutral category and to Klein and Ford's impersonal–independent category.

For parts of our study we treat time spent with the Internet as an aggregate:

- *Internet*: time spent by the respondent obtaining any information conveyed on the Internet, including ratings/price data/ads/manufacturer data/dealer data/online chat/the Internet version of *Consumer Reports.*

### *Measures of Internet Search*

In addition to the general measures of search, the detailed list of measures of Internet search provided in Table 3.2 was collected in the 2002 survey. This list covers specific Internet sources: manufacturer, dealer, auto buying services (e.g., Autobytel), third-party sources (the online counterpart of offline nonadvocate sources), and bulletin board/chat sources. This list of Internet sources coincides with the one defined by Klein and Ford (2003). For the major types of Internet sources related to automobile buying, we asked questions about number of sites consulted, time spent with each type, how much information was obtained from each site, and how helpful each site was. These questions are meant to measure the breadth, depth,

Table 3.2

**Measures of Internet Search Included in 2002 Survey[a]**

In deciding which car to buy and which dealer to purchase it from, number of Web sites personally checked from each of the following Internet sources:

- Manufacturer Web sites (e.g., www.ford.com)
- Dealer Web sites (e.g., www.buffalochrysler.com)
- Auto buying services online (e.g., www.autobytel.com)
- Third-party information services online (e.g., www.consumerreports.org)
- Bulletin board/chat online (e.g., Yahoo Auto)

Time spent checking for information on the Internet for your recent new car for:

- Manufacturer Web sites (e.g., www.ford.com)
- Dealer Web sites (e.g., www.buffalochrysler.com)
- Auto buying services online (e.g., www.autobytel.com)
- Third-party information services online (e.g., www.consumerreports.org)
- Bulletin board/chat online (e.g., Yahoo Auto)

When visiting different Web sites, how much of the following types of information did you obtain (six-point scale ranging from No Information to A Lot of Information):

- Price information
- Performance information
- Reliability information
- Referral to dealer for a price quote
- Other buyers' experience/recommendation
- Trade-in value

When deciding which car to buy and which dealer to purchase it from, how helpful was the information that you got from each of the following Web sites (seven-point scale ranging from Not Very Helpful to Extremely Helpful):

- Manufacturer Web sites
- Dealer Web sites
- Auto buying services online
- Third-party information services online
- Bulletin board/chat online

[a]Answered only by those who personally consulted the Internet for information about cars or dealers.

and usefulness of each type of Internet site. Patterns of response to these questions will reveal different types of Internet search.

*Independent Variables*

Our independent variables consist of measures of amount and content of experience, demographics, prior information, and Internet access. The measures of whether respondents knew which manufacturer or dealer they wanted to buy from before engaging in search provide direct measures of prior information. In the analysis these were coded as: definitely yes = 1, 0 otherwise. The measures of first car owned and number of new cars bought in past 10 years provide measures of the respondent's amount of experience. Content of experience is measured by the questions about satisfaction with previous car and dealer. Income is self-reported annual household income, with the 1989 data inflated to 2001 values. Education is measured as years of school completed. Our age measure consisted of variables for the following categories: 18–20, 21–30, 31–40, 41–50, 51–60, 61 and above. In addition to these measures, we included other demographics, such as gender, marital status (married or not), and employment status of respondent.

Table 3.3

**Description of Samples: Independent Variables**

| | Sample | | 1989–2001 difference | | 2001 Sample | | Difference between users and nonusers | |
|---|---|---|---|---|---|---|---|---|
| Variable | 1989 | 2001 | *t* value | Pr > \|*t*\| | Not use Internet | Use Internet | *t* value | Pr > \|*t*\| |
| Knew manufacturer | 0.467 | 0.543 | 2.98 | 0.00 | 0.678 | 0.453 | 6.04 | <.0001 |
| Knew dealer | 0.265 | 0.356 | 3.91 | <.0001 | 0.537 | 0.235 | 8.64 | <.0001 |
| First car bought | 0.017 | 0.030 | 1.74 | 0.08 | 0.018 | 0.038 | –1.55 | 0.12 |
| Satisfied manufacturer | 5.374 | 5.592 | 2.62 | 0.01 | 5.723 | 5.504 | 1.91 | 0.06 |
| Satisfied dealer | 5.155 | 5.395 | 2.94 | 0.00 | 5.700 | 5.190 | 4.57 | <.0001 |
| New cars bought past 10 years | 1.934 | 2.340 | 4.69 | <.0001 | 2.597 | 2.168 | 3.02 | 0.00 |
| Years schooling | 14.748 | 15.173 | 2.87 | 0.00 | 14.496 | 15.628 | –5.33 | <.0001 |
| HH income[a] | 60487 | 64466 | 2.35 | 0.02 | 62569 | 65739 | –1.40 | 0.16 |
| Male | 0.675 | 0.572 | –4.21 | <.0001 | 0.537 | 0.595 | –1.52 | 0.13 |
| Married | 0.692 | 0.662 | –1.22 | 0.22 | 0.693 | 0.642 | 1.39 | 0.17 |
| Employed | 0.762 | 0.807 | 2.16 | 0.03 | 0.686 | 0.889 | –6.91 | <.0001 |
| Spouse employed | 0.405 | 0.495 | 3.58 | 0.00 | 0.470 | 0.512 | –1.09 | 0.28 |
| Age 20 or Less | 0.009 | 0.011 | 0.36 | 0.72 | 0.007 | 0.014 | –0.88 | 0.38 |
| Age 21–30 | 0.152 | 0.159 | 0.38 | 0.70 | 0.095 | 0.201 | –3.81 | 0.00 |
| Age 31–40 | 0.214 | 0.183 | –1.50 | 0.13 | 0.134 | 0.216 | –2.75 | 0.01 |
| Age 41–50 | 0.212 | 0.282 | 3.20 | 0.00 | 0.251 | 0.303 | –1.52 | 0.13 |
| Age 51–60 | 0.160 | 0.207 | 2.39 | 0.02 | 0.230 | 0.192 | 1.21 | 0.23 |
| Age 61 or More | 0.247 | 0.157 | –4.35 | <.0001 | 0.283 | 0.073 | 7.78 | <.0001 |
| Measures of Internet access | | | | | | | | |
| Internet at home | | | | | 0.569 | 0.917 | –11.93 | <.0001 |
| Internet elsewhere | | | | | 0.696 | 0.884 | –6.22 | <.0001 |
| Years Internet use | | | | | 2.375 | 5.017 | –12.03 | <.0001 |
| Hrs/wk Internet on job | | | | | 3.774 | 4.756 | –1.65 | 0.10 |
| Hrs/wk Internet non-job | | | | | 4.139 | 5.979 | –2.69 | 0.01 |
| Number PC at home | | | | | 1.119 | 1.569 | –5.98 | <.0001 |
| Sample size | | 843 | 705 | | 283 | 422 | | |

[a]Measured in constant dollars.

### *Descriptive Results*

To facilitate the interpretation of empirical analyses to be presented later, and to describe how search behavior has changed with the advent of the Internet, we will describe the characteristics of the samples employed in this study and their search behavior. Table 3.3 presents mean values for the two samples and for Internet users and nonusers in the sample of 2001 buyers. Compared to the 1989 buyers, the 2001 buyers bought more new cars in the past 10 years, are more educated,

Table 3.4

**Description of Samples: Search Behavior**

| Variable | Sample 1989 | Sample 2001 | 1989–2001 difference *t* value | 1989–2001 difference Pr > \|*t*\| | 2001 sample Not use Internet | 2001 sample Use Internet | Difference between users and nonusers 2001 | Difference between users and nonusers *t* value |
|---|---|---|---|---|---|---|---|---|
| Hours with: | | | | | | | | |
| Friend/relative | 2.117 | 1.784 | –1.64 | 0.10 | 1.562 | 1.933 | –1.25 | 0.21 |
| Nonadvocate | 2.530 | 1.758 | –4.00 | <.0001 | 1.149 | 2.167 | –4.24 | <.0001 |
| Books | 1.320 | 0.917 | –3.73 | 0.00 | 0.706 | 1.058 | –2.40 | 0.02 |
| Car ratings | 1.210 | 0.842 | –3.33 | 0.00 | 0.442 | 1.110 | –4.65 | <.0001 |
| Advertising | 1.801 | 1.563 | –1.58 | 0.11 | 1.256 | 1.769 | –2.47 | 0.01 |
| Ads | 0.956 | 0.723 | –1.95 | 0.05 | 0.661 | 0.765 | –0.65 | 0.51 |
| Brochures | 0.845 | 0.840 | –0.07 | 0.94 | 0.595 | 1.004 | –3.67 | 0.00 |
| Dealer | 12.196 | 9.103 | –5.30 | <.0001 | 7.057 | 10.475 | –4.58 | <.0001 |
| Travel | 3.384 | 2.684 | –2.84 | 0.00 | 2.098 | 3.077 | –2.44 | 0.02 |
| Showroom | 2.819 | 1.686 | –6.53 | <.0001 | 1.218 | 1.999 | –4.04 | <.0001 |
| Salespeople | 2.749 | 2.061 | –4.57 | <.0001 | 1.730 | 2.283 | –3.39 | 0.00 |
| Negotiating | 1.815 | 1.412 | –3.68 | 0.00 | 1.196 | 1.557 | –2.53 | 0.01 |
| Test drives | 1.429 | 1.260 | –1.63 | 0.10 | 0.814 | 1.560 | –4.88 | <.0001 |
| Total non-Internet | 18.644 | 14.208 | –5.17 | <.0001 | 11.023 | 16.345 | –5.00 | <.0001 |
| Internet | 0.000 | 2.129 | | | 0.000 | 3.557 | | |
| Total | 18.644 | 16.338 | | | 11.023 | 19.902 | –7.54 | <.0001 |
| Shares of non-Internet hours | | | | | | | | |
| Friend/relative | 0.099 | 0.132 | 4.79 | <.0001 | 0.149 | 0.121 | 2.26 | 0.02 |
| Nonadvocate | 0.118 | 0.110 | –1.10 | 0.27 | 0.089 | 0.125 | –3.24 | 0.00 |
| Advertising | 0.088 | 0.101 | 2.65 | 0.01 | 0.095 | 0.105 | –1.29 | 0.20 |
| Dealer | 0.696 | 0.657 | –3.58 | 0.00 | 0.668 | 0.650 | 1.02 | 0.31 |
| Internet share | | | | | 0.000 | 0.179 | | |
| N | 843 | 705 | | | 283 | 422 | | |

have a higher real income, are more likely to be female, are more likely to be employed, and are less likely to be age 61 or more. Many of these differences undoubtedly represent changes in the local population over this period. In addition, the 2001 buyers are more likely to be satisfied with their previous purchase and more likely to have decided on a manufacturer or dealer prior to the search. Approximately 60% of the 2001 buyers report using the Internet, which is consistent with J.D. Power data for this period, and a 50% increase over the approximately 40% of Internet users in our 1999 sample (Ratchford, Lee, and Talukdar, 2003). Compared to the nonusers, the Internet users in our sample are younger, more educated, and more likely to be employed, and bought fewer cars in the past 10 years (a measure of experience). Importantly, the Internet users tend to be less satisfied, especially with their previous dealer, and less likely to have decided on a manufacturer or dealer prior to the search. In short, they have less prior information than the nonusers.

The search behavior of the various groups on the individual time measures is described in Table 3.4. In general, the reported hours of search declined between 1989 and 2001. While some of the decline could have been due to efficiencies introduced by the Internet, the data in the preceding table indicated that the 2001 sample had more prior information (higher pre-search decision on manufacturer and dealer, higher satisfaction, more buying experience), which could also lower search. There were also several demographic differences between the samples. The share of non-Internet hours of the friend/relative and advertising sources increased significantly

Table 3.5

**Characteristics of Internet Use: Internet Users**

| Useable characteristic | Sample size | Mean |
|---|---|---|
| Search time-Internet | 422 | 3.557 |
| Pct time manufacturer sites | 372 | 42.78% |
| Pct time dealer sites | 372 | 17.29% |
| Pct time buying service sites | 372 | 18.25% |
| Pct time third-party services | 372 | 17.33% |
| Pct time bulletin board/chat sites | 372 | 4.35% |
| Time manufacturer sites | 372 | 1.530 |
| Time dealer sites | 372 | 0.588 |
| Time buying service sites | 372 | 0.639 |
| Time third-party services | 372 | 0.836 |
| Time bulletin board sites | 372 | 0.205 |
| Amt Web price information[a] | 422 | 3.358 |
| Amt Web performance information[a] | 422 | 3.284 |
| Amt Web reliability information[a] | 422 | 2.981 |
| Amt Web referral price quote information[a] | 422 | 1.742 |
| Amt Web other buyer experience information[a] | 422 | 1.455 |
| Amt Web trade in value information[a] | 422 | 1.865 |
| Amt Web other information[a] | 422 | 0.495 |
| Number manufacturer sites consulted | 422 | 2.028 |
| Number dealer sites consulted | 422 | 1.382 |
| Number buying service sites consulted | 422 | 0.974 |
| Number third-party sites consulted | 422 | 0.938 |
| Number bulletin board/chat sites consulted | 422 | 0.239 |
| Total number Web sites consulted | 422 | 5.562 |
| Sites consulted per hour | 422 | 2.245 |
| Helpfulness of manufacturer Web sites[b] | 418 | 3.974 |
| Helpfulness of dealer Web sites[b] | 415 | 2.752 |
| Helpfulness of online buying services[b] | 414 | 2.676 |
| Helpfulness of third-party information services[b] | 411 | 2.959 |
| Helpfulness of bulletin board/chat services[b] | 417 | 1.468 |

[a]Measured on a 6-point scale, 0 = no information, . . . , 5 = a lot of information.
[b]Measured on a 7-point scale, 1 = not very helpful, . . . , 7 = extremely helpful.

between 1989 and 2001, while the dealer share of these hours declined significantly. We will test later whether this was due to the influence of the Internet.

Table 3.4 also presents a comparison of time expenditures between Internet users and nonusers. In general, Internet users search a lot more than nonusers. However, the Internet users are generally of the type that would search a lot: they had a lower rate of pre-search decisions on manufacturer and dealer, they were less satisfied with their previous manufacturer and dealer, they had less experience at buying cars, and they were younger and more educated. Among users, the Internet is the second most utilized source after the dealer. In comparison to nonusers, Internet users had a lower share of non-Internet hours for friend/relative, but a higher share of non-Internet hours for nonadvocate. Again we will test whether this change in shares was due to the presence of the Internet.

Table 3.5 presents a description of the characteristics of Internet use. Internet users report spending more time at manufacturer sites than at other sites. They also rate manufacturer sites as most helpful on average. Dealer sites, buying service sites, and third-party sites have about the same average share of time, but third-party sites have the highest average time among these three. This indicates that the third-party sites tend to be used most extensively by those who have the highest total amount of time spent with the Internet. The third-party sites are also rated as second most helpful on average. Our data indicate that Internet users consult an average of 5 to 6 Web sites, or about 2.2 sites per hour spent. Where comparable data are presented, these findings on utilization of different Internet sites are consistent with Klein and Ford (2003). As to what information respondents obtain from the Internet, price has the highest average, followed by performance and reliability. Later in this chapter we will examine the relationship between information obtained and time spent with different types of Internet sites.

### Test for Proportional Draw

Consider the share of non-Internet hours before and after the introduction of the Internet. As stated earlier, we can estimate the cross-sectional variation in this share with respondent characteristics **H** on pre-Internet data. Denoting this estimate as  we can estimate a predicted non-Internet share for each current respondent: Then our test becomes:

$H_o$: $$\Delta s_{kh} = s_{kh1} - \hat{s}_{kh0} = \hat{\varepsilon}$$

$H_a$: $$\Delta s_{kh} = s_{kh1} - \hat{s}_{kh0} = \hat{\varepsilon} + d(t_I)$$

Thus, if the difference between predicted and actual share is related to Internet time, or time with any specific Internet source, the null hypothesis is rejected.

The first step in this analysis is to estimate the baseline relationship between shares and respondent characteristics. Because of the presence of a substantial number of zero shares, we use the tobit regression model for this purpose. Results for tobit regressions on data for 1989 buyers are presented in Table 3.6 for shares of friend/relative, nonadvocate, and advertising. Since shares must add to one, the dealer share equation is redundant, and the dealer share can be determined by subtraction.

While the estimates in Table 3.6 have relatively low R-squares, which is typical for analyses of the use of sources (Ratchford, Lee, and Talukdar, 2003; Klein and Ford, 2003), the results tell a story that is broadly consistent with other findings on search for automobiles in the literature (Kiel and Layton, 1981, Furse, Punj, and Stewart, 1984). As Table 3.6 indicates, the share of the friend/relative source varies inversely with experience (new cars bought in past 10 years), education, income, and age. The share of the nonadvocate source is related to incentives to search for a manufacturer (no pre-decision on manufacturer, low satisfaction with previous manufacturer), and positively related to education. Like the friend/relative source, the share of the advertising source varies inversely with experience; the share of this source is also positively related to satisfaction with the previous dealer.

Using the estimates in Table 3.6, a predicted pre-Internet share was computed for each 2001 buyer as $\hat{s}_{kh0} = \hat{f}(\mathbf{H})$. Then the difference between predicted and actual shares was computed as $\Delta s_{kh} = s_{kh1} - \hat{s}_{kh0}$. Regressions of this difference on various measures of Internet activity were then employed in testing the proportional draw hypothesis as outlined above. The results, which are presented in Table 3.7, indicate that overall Internet time is associated with a reduction of the share of the friend/relative source below its expected value, indicating that the Internet and

Table 3.6

**Tobit Regressions of Shares of Time on Determinants: 1989 Buyers**

| | Share friend/relative | | Share nonadvocate | | Share advertising | |
|---|---|---|---|---|---|---|
| Variable | Coefficient | *t* value | Coefficient | *t* value | Coefficient | *t* value |
| Primary index equation for model | | | | | | |
| Constant | **0.21382** | **6.04** | 0.02753 | 0.70 | **0.10692** | **3.96** |
| Knew manufacturer | 0.00204 | 0.18 | **–0.03304** | **–2.52** | –0.00643 | –0.73 |
| Knew dealer | –0.02395 | –1.82 | –0.00419 | –0.28 | –0.00999 | –1.00 |
| Satisfied manufacturer | 0.00330 | 1.00 | **–0.00762** | **–2.05** | –0.00460 | –1.82 |
| Satisfied dealer | –0.00004 | –0.01 | –0.00246 | –0.66 | **0.00592** | **2.31** |
| New cars bought past 10 Years | **–0.01424** | **–3.93** | –0.00434 | –1.07 | **–0.00670** | **–2.45** |
| Years schooling | **–0.00386** | **–2.12** | **0.00790** | **3.86** | –0.00179 | –1.28 |
| Married | –0.01562 | –1.25 | 0.00709 | 0.50 | 0.00750 | 0.78 |
| HH income/$10,000 | **–0.00437** | **–2.59** | 0.00039 | 0.21 | 0.00099 | 0.78 |
| Male | –0.01997 | –1.70 | 0.02092 | 1.55 | 0.00571 | 0.63 |
| Age 20 or less | –0.02819 | –0.54 | 0.00998 | 0.17 | 0.03538 | 0.88 |
| Age 21–30 | 0.00426 | 0.25 | –0.00515 | –0.26 | –0.01219 | –0.92 |
| Age 31–40 | 0.00745 | 0.50 | 0.00731 | 0.43 | –0.00085 | –0.07 |
| Age 51–60 | –0.03219 | –1.94 | 0.01831 | 0.98 | **–0.02839** | **–2.24** |
| Age 61 or more | **–0.06853** | **–4.31** | –0.00550 | –0.31 | –0.01425 | –1.19 |
| Disturbance standard deviation | | | | | | |
| Sigma | **0.13747** | **32.65** | **0.15669** | **32.74** | **0.10709** | **34.33** |
| R-squared | 0.08176 | | 0.05666 | | 0.03470 | |

*Note:* Sample size = 843. Coefficients that are significant at .05 are in bold.

Table 3.7

**Relations Between Expected Share of Time and Internet Use**

| | Dependent variable is 2001 actual–expected based on 1989 Tobit coefficients | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Friend/relative | | Nonadvocate | | Advertising | | Dealer | |
| Variable | Coefficient | *t* value | Coefficient | *t* value | Coefficient | *t* value | Coefficient | *t* value |
| Regression 1 | | | | | | | | |
| Intercept | **0.04653** | **5.84** | –0.01219 | –1.71 | **0.01180** | **2.28** | **–0.04614** | **–4.02** |
| Ln(Internet time) | **–0.01825** | **–2.46** | 0.01032 | 1.56 | 0.00460 | 0.96 | 0.00332 | 0.31 |
| R-squared | **0.00850** | | 0.00340 | | 0.00130 | | 0.00010 | |
| Regression 2 | | | | | | | | |
| Intercept | **0.04067** | **5.54** | –0.00989 | –1.53 | **0.01309** | **2.74** | **–0.04388** | **–4.15** |
| Ln(Int mfr time) | 0.01561 | 1.19 | –0.02043 | –1.76 | 0.00716 | 0.84 | –0.00234 | –0.12 |
| Ln(Int dlr time) | –0.00527 | –0.27 | –0.00794 | –0.47 | –0.01050 | –0.84 | 0.02370 | 0.86 |
| Ln(Int buy service time) | –0.02724 | –1.61 | –0.00055 | –0.04 | 0.00273 | 0.25 | 0.02506 | 1.03 |
| Ln(Int 3rd party time) | –0.03002 | –1.91 | **0.05331** | **3.85** | 0.00461 | 0.45 | –0.02790 | –1.23 |
| Ln(Int BB/chat time) | –0.02085 | –0.70 | **0.06777** | **2.59** | –0.00176 | –0.09 | –0.04515 | –1.06 |
| R-squared | **0.01610** | | **0.03920** | | 0.00210 | | 0.00630 | |

*Note:* Sample size = 705. Coefficients that are significant at .05 are in bold.

friend/relative are more substitutable than would be predicted by proportional draw. However, while this relationship is statistically significant, the associated R-squared value is very low (.00850). Using Internet time as the measure of Internet use, the proportional draw hypothesis cannot be rejected for the other three sources.

The second panel tests whether specific Internet sources have a relationship with $\Delta.s_{kh}$. The only relationships that are significant at the .05 level are that Internet third-party time and Internet bulletin board/chat time are both positively related to deviations from expected nonadvocate share. The interpretation is that the Internet third-party and Internet bulletin board/chat sources are more complementary to the conventional nonadvocate than predicted by the proportional draw hypothesis. Again the R-squared values for specific Internet sources are low, and two are insignificant at the .05 level. Our conclusion is that, although proportional draw is violated in some instances, the violations are not major. So, the assumption that the Internet draws in equal proportion from other sources is likely to be a good approximation for the aggregate categories of major non-Internet information sources considered in this study.

However, a valid question of interest is whether the approximation continues to hold for a finer breakdown of the information sources. In particular, price information obtained on the Internet may disproportionately reduce the share of negotiation time at the dealer, and performance information obtained on the Internet may disproportionately reduce the share of test drive time. To test these hypotheses, we employed the methodology outlined above of regressing deviations from predicted shares on various measures of Internet use. Table 3.8 presents the results of tobit regressions on share of negotiation and test drive time that were used in developing baseline predictions. As indicated in Table 3.8, those with a high share of time spent in negotiations with the dealer tend to have made a pre-decision on manufacturer, tend to be experienced at buying cars, and tend to be age 61 or more. These are not the types that are likely to use the Internet. As shown in Table 3.8, those with a high share of time spent with test drives tend to have a high income. Using predictions developed from the coefficients in Table 3.8, differences between actual and expected negotiation and test drive time were regressed on various measures of Internet use. As shown in Table 3.9, there are no statistically significant relationships between these differences and the measures of Internet use. We conclude that the Internet does substitute for negotiation and test drives in approximate proportion to their original shares of time.

## Information Produced by Internet Sources

As shown in Table 3.2, we have data on types of information that buyers report obtaining from the Internet, in the form of 6-point scales ranging from no information to a lot of information. Relationships between these types of information and the use of specific Internet sources would aid in understanding what types of information are produced by different Internet sources and in understanding what these sources are used for. Specifically, as explained earlier, coefficients in regressions of information obtained on the log of time spent with each Internet source could be interpreted as measuring information produced by each source if the proportional draw hypothesis is a reasonable approximation.

The results of these regressions are presented in Table 3.10 on page 102. Given the common scale of the independent variables, the coefficients can be interpreted as reflecting the relative impact of the different sources on different types of information. The results show clear differences in effects, which can be ranked as follows (rankings limited to significant coefficients):

Price information: manufacturer, buying service, third party.
Performance information: manufacturer, third party, buying service.

Table 3.8

**Tobit Regresssions for Share of Negotiation and Test Drives Time: 1989 Sample**

| | Share negotiation | | Share test drives | |
|---|---|---|---|---|
| Variable | Coefficient | *t* value | Coefficient | *t* value |
| Primary index equation for model | | | | |
| Constant | **0.07480** | **2.63** | **0.06375** | **3.31** |
| Knew manufacturer | **0.02298** | **2.46** | –0.00606 | –0.95 |
| Knew dealer | 0.01134 | 1.08 | 0.01385 | 1.94 |
| Satisfied manufacturer | 0.00274 | 1.02 | 0.00100 | 0.55 |
| Satisfied dealer | –0.00073 | –0.27 | –0.00047 | –0.26 |
| New cars bought past 10 Years | **0.00653** | **2.27** | –0.00261 | –1.33 |
| Years schooling | 0.00045 | 0.31 | 0.00070 | 0.70 |
| Married | 0.01264 | 1.24 | 0.00709 | 1.03 |
| HH income/$10,000 | –0.00208 | –1.56 | **0.00247** | **2.73** |
| Male | –0.00537 | –0.56 | –0.00584 | –0.90 |
| Age 20 or less | –0.04624 | –1.06 | –0.02749 | –0.94 |
| Age 21–30 | 0.00427 | 0.30 | –0.01145 | –1.19 |
| Age 31–40 | –0.00247 | –0.20 | –0.00226 | –0.27 |
| Age 51–60 | 0.00824 | 0.62 | –0.01069 | –1.18 |
| Age 61 or more | **0.03379** | **2.67** | –0.00766 | –0.89 |
| Disturbance standard deviation | | | | |
| Sigma | **0.11603** | **39.68** | **0.07860** | **38.78** |
| R-squared | 0.04305 | | 0.02425 | |

*Note:* Sample size = 843. Coefficients that are significant at .05 are in bold.

Table 3.9

**Relations Between Expected Share of Time and Internet Use for Negotiation and Test Drives**

| | Dependent variable is 2001 actual–expected based on 1989 Tobit coefficients | | | |
|---|---|---|---|---|
| | Dealer negotiation | | Test drives | |
| Variable | Coefficient | *t* value | Coefficient | *t* value |
| Regression 1 | | | | |
| Intercept | **–0.01699** | **–3.13** | 0.00526 | 0.98 |
| Ln(Internet time) | –0.00510 | –1.01 | 0.00061 | 0.12 |
| R-squared | 0.00150 | | 0.00000 | |
| Regression 2 | | | | |
| Intercept | **–0.01929** | **–3.86** | 0.00562 | 1.14 |
| Ln(Int mfr time) | –0.00048 | –0.05 | 0.00166 | 0.19 |
| Ln(Int dlr time) | –0.02016 | –1.54 | –0.01314 | –1.02 |
| Ln(Int buy service time) | 0.01518 | 1.32 | 0.00018 | 0.02 |
| Ln(Int third party time) | –0.00010 | –0.01 | 0.00753 | 0.71 |
| Ln(Int BB/chat time) | –0.00757 | –0.38 | 0.00453 | 0.23 |
| R-squared | 0.00570 | | 0.00220 | |

*Note:* Sample size = 705. Coefficients that are significant at .05 are in bold.

Reliability information: third party, buying service, manufacturer.
Referral and price quote information: dealer.
Others' experiences: bulletin board/chat, third party, buying service, manufacturer.
Trade-in value: buying service, third party.

At first glance it might seem surprising that buying services are significantly related to all types of information except referral and price quote. A closer look, however, suggests that this finding is, in fact, reasonable. As an example, Autobytel provides detailed information on a complete list of new makes and models, including ratings and reviews by other buyers, and it also provides extensive information on trade-in values and used car prices. Although Autobytel is in the business of providing referrals to dealers, the actual price quotes from the dealers obtained through Autobytel come offline. Whereas most of the other findings in Table 3.10 might be anticipated, the other noteworthy result is that manufacturer Web sites appear to be a major source of price information.

Table 3.10 provides insights into what types of information are obtained from the different sources, but it is also important to determine the types of Internet information that are obtained by consumers with different characteristics. To accomplish this, we regressed the reported amounts of information obtained for each category on respondent characteristics (the regressions are limited to Internet users). The results, which are reported in Table 3.11, show that uncertainty about dealer to buy from has the most significant relationship to price, performance, and reliability information. Internet users who are age 61 or more generally report obtaining less information from the Internet than other age groups. Conversely, respondents who are age 21–30 report obtaining significantly more Internet information about referrals and price quotes, and about others' experiences than other age groups. The latter finding may reflect the tendency of consumers to substitute the Internet for friends and relatives that was observed earlier. The amount of price information obtained from the Internet is significantly related to education, while the amount of referral and price quote information is inversely related to income. The latter finding may reflect a higher degree of price sensitivity on the part of consumers with lower incomes.

## Conclusions

Our major findings relate to substitution patterns between the Internet and other sources and to the use of different Internet sources. We have expanded the test of proportional draw in our earlier (Ratchford, Lee, and Talukdar, 2003) paper to a more detailed list of sources, and have found that this assumption is likely to be a good approximation for use in empirical work. The substantive implication of this finding is that the Internet tends to draw time from other sources in approximate proportion to their original share of use. Consequently, the Internet is a substitute for other sources. An explanation for these results is provided by Klein and Ford (2003), who note that information provided by the Internet overlaps that provided by each of the other sources. We do find some significant instances of violation of the proportional draw hypothesis. The Internet appears to be more of a substitute for friends/relatives than predicted by proportional draw, and Internet third party and bulletin board/chat sources appear to be less of a substitute for nonadvocate sources than predicted by proportional draw. Although the proportional draw hypothesis naturally relates to shares, in absolute terms the Internet has the largest impact on the use of dealer-related sources, since these get the largest share of time. While it is possible that proportional draw would not hold for finer breakdowns of sources than used in this study, we find that this hypothesis cannot be rejected for negotiations and test drives. The results for negotiations may be

Table 3.10

**Regressions of Self-Reported Information Obtained from the Internet on Different Topics on Time with Each Web Source**

| | Internet time use | | | | | | |
|---|---|---|---|---|---|---|---|
| | Intercept | Ln(mfr time) | Ln(dealer time) | Ln(buy service time) | Ln(third party time) | Ln(BB/chat time) | R-squared |
| Price information | | | | | | | |
| Coefficient | **2.5604** | **0.8054** | 0.2266 | **0.5277** | **0.3161** | 0.3431 | **0.1953** |
| $t$ value | **24.16** | **6.27** | 1.28 | **3.32** | **2.17** | 1.21 | |
| Performance information | | | | | | | |
| Coefficient | **2.6171** | **0.6251** | 0.0454 | **0.3416** | **0.6026** | 0.1661 | **0.1605** |
| $t$ value | **24.88** | **4.91** | 0.26 | **2.17** | **4.16** | 0.59 | |
| Reliability information | | | | | | | |
| Coefficient | **2.3352** | **0.4283** | 0.1773 | **0.4287** | **0.6957** | 0.1926 | **0.1453** |
| $t$ value | **20.86** | **3.16** | 0.95 | **2.56** | **4.51** | 0.64 | |
| Referral and price quote | | | | | | | |
| Coefficient | 1.3 | 0.2196 | **0.7088** | 0.2797 | 0.0364 | 0.5033 | **0.0754** |
| $t$ value | 10.91 | 1.52 | **3.56** | 1.57 | 0.22 | 1.58 | |
| Others' experiences | | | | | | | |
| Coefficient | 0.9646 | **0.3431** | –0.0019 | **0.3651** | **0.4431** | **0.6495** | **0.0944** |
| $t$ value | 8.98 | **2.64** | –0.01 | **2.27** | **2.99** | **2.26** | |
| Trade-in value informatiom | | | | | | | |
| Coefficient | 1.3629 | 0.1164 | 0.1335 | **0.691** | **0.5061** | 0.1984 | **0.0826** |
| $t$ value | 10.69 | 0.75 | 0.63 | **3.62** | **2.88** | 0.58 | |

*Note:* Sample size = 442. Coefficients that are significant at .05 are in bold.

influenced by the fact that those who spend the highest share of time in negotiations are older, more experienced consumers of the type that are unlikely to be Internet users.

We have obtained detailed evidence about the use and information output of different Internet sources for automobile information. One of our key findings is the importance of the manufacturer source. This source gets the highest average share of time from Internet users; the average number of manufacturer sources consulted is over two, indicating that competitive information is commonly sought; and the manufacturer source appears to be a major producer of price, performance, and reliability information. Thus, a well-designed manufacturer Web site appears to be critical, particularly for cars aimed at younger, more educated buyers, who tend to use the Internet. Aside from the manufacturer, third-party sources and buying services appear to be important producers of most types of Internet information about automobiles. Uncertainty about dealer to buy from is prominently related to acquisition of price, performance, and reliability information on the Internet. Possibly the Internet is used as a source when there is no trusted dealer available for obtaining the information.

## Future Research

Our literature review and analysis raise a number of issues that might be addressed in future research. One is methodological. With the exception of the laboratory study of Hauser, Urban, and Weinberg (1993) and the panel data studies of studies of Strebel, Erdem, and Swait (2004), and Erdem, Keane, and Strebel (2004), studies of the use of information sources in general, and of the use of the Internet as an information source in particular, have relied primarily on survey data. This survey data have been collected either during the search (Klein and Ford 2003) or, more typically, after the purchase (Klein and Ford, 2003; Ratchford, Lee, and Talukdar, 2003; and the present study, Scott Morton, Zettelmeyer, and Silva-Risso, 2004).

The survey method is an accepted method of data collection, but it has two major weaknesses: it relies heavily on respondent ability to recall past events, and it does not readily allow one to trace the search process through time. Though much more difficult to collect, panel data of the type employed by Strebel, Erdem, and Swait (2004), and Erdem, Keane, and Strebel (2004) overcomes both of these problems. More use of panels for data collection in studies of search behavior should be investigated. A major challenge in setting up such panels will be to identify persons who are in the market for the focal item. In the case of search for items that are not likely to be purchased by those without Internet access, prospective purchasers could be recruited on the Internet, and waves of panel surveys could be collected there.

Another methodological issue is that little is known about the accuracy of consumer self- reports of search behavior. Although the self-reports generally produce results that agree with expectations and are consistent across studies, they rely extensively on ability to recall past events, and are subject to social acceptability biases. One way to test the accuracy of self-reports would be to compare self-reported Internet use with click-stream data on actual use (Johnson et al., 2004).

A number of questions that might be addressed in future research arise from our analysis. Although Scott Morton, Zettelmeyer, and Silva-Risso (2004) have provided clear evidence of the impact of the Internet on automobile prices, not much is known about whether the presence of the Internet also leads to better buys—purchase of items that better fit one's needs. One possible direction to take in addressing this question would be to determine whether there is a measurable relation between use of the Internet, or obtaining specific types of information on the Internet, and actual choice of a car. Lack of such a relationship would lead one to conclude that the Internet does not lead to better buys. To further investigate the impact of the Internet, one might investi-

Table 3.11

**Relation Between Information Obtained from the Internet and Consumer Characteristics**

| | Price information | | Performance information | | Reliability information | | Referral and price quote | | Others' experiences | | Trade-in value information | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Coefficient | *t* value | Coefficient | *t* value | Coefficient | *t* value | Coefficient | *t* value | Coefficient | *t* value | Coefficient | *t* value |
| Intercept | **2.1186** | **3.50** | **2.2053** | **3.74** | **2.2097** | **3.55** | 0.8236 | 1.29 | 1.0019 | 1.72 | **1.6111** | **2.31** |
| Knew manufacturer | 0.2125 | 1.22 | 0.0357 | 0.21 | 0.0630 | 0.35 | 0.2045 | 1.12 | 0.0006 | 0.00 | 0.1902 | 0.95 |
| Knew dealer | **–0.6336** | **–3.10** | **–0.5653** | **–2.84** | **–0.7245** | **–3.45** | –0.1768 | –0.82 | –0.3666 | –1.87 | –0.3764 | –1.60 |
| Satisfied manufacturer | 0.0403 | 0.73 | 0.0447 | 0.83 | 0.0453 | 0.79 | –0.0058 | –0.10 | –0.0650 | –1.22 | 0.0058 | 0.09 |
| Satisfied dealer | 0.0124 | 0.21 | 0.0039 | 0.07 | 0.0319 | 0.53 | 0.0207 | 0.33 | 0.0900 | 1.59 | –0.1175 | –1.73 |
| New cars bought past 10 years | –0.0193 | –0.40 | 0.0284 | 0.61 | –0.0052 | –0.10 | 0.0254 | 0.50 | –0.0012 | –0.03 | 0.0001 | 0.00 |
| Years schooling | **0.0677** | **2.20** | 0.0537 | 1.79 | 0.0312 | 0.99 | 0.0540 | 1.67 | 0.0170 | 0.58 | 0.0280 | 0.79 |
| Married | 0.0832 | 0.44 | 0.0557 | 0.30 | 0.1316 | 0.67 | 0.2062 | 1.03 | 0.3200 | 1.75 | 0.2110 | 0.97 |
| HH income/$10,000 | –0.0220 | –0.71 | –0.0111 | –0.36 | –0.0035 | –0.11 | **–0.0714** | **–2.16** | –0.0335 | –1.12 | 0.0044 | 0.12 |
| Male | 0.0261 | 0.15 | 0.0155 | 0.09 | –0.1281 | –0.72 | –0.0271 | –0.15 | 0.1192 | 0.72 | 0.0102 | 0.05 |
| Age 20 or less | 0.7137 | 1.00 | 0.2545 | 0.37 | 0.0497 | 0.07 | 1.2814 | 1.70 | 0.7132 | 1.04 | –0.0078 | –0.02 |
| Age 21-30 | 0.3066 | 1.24 | 0.2904 | 1.21 | 0.3423 | 1.35 | **0.7037** | **2.71** | **0.5655** | **2.39** | 0.3228 | 1.22 |
| Age 31-40 | 0.2648 | 1.17 | 0.2454 | 1.11 | 0.1614 | 0.69 | 0.4685 | 1.96 | 0.1962 | 0.90 | 0.4232 | 1.62 |
| Age 51-60 | –0.0288 | –0.13 | 0.0718 | 0.32 | 0.0113 | 0.05 | 0.1554 | 0.64 | –0.0001 | 0.00 | 0.2970 | 1.05 |
| Age 61 or more | **–0.7323** | **–2.26** | **–0.8265** | **–2.61** | **–0.7487** | **–2.24** | –0.5160 | –1.51 | **–0.7271** | **–2.34** | –0.3242 | –0.39 |
| R-squared | **0.0705** | | **0.0661** | | **0.0645** | | **0.0604** | | **0.0633** | | **0.0329** | |

*Note:* Sample size = 442. Coefficients that are significant at .05 are in bold.

gate whether there is a positive relationship between Internet use, or specific Internet information types, and *Consumer Reports* ratings or recommendations. We have data on car chosen and consideration sets and may be able to address these questions.

While we have looked at allocation of search time across sources, total time spent is also important. Given more detailed data on types of Internet source use than was available for our earlier (2003) analysis, another extension of this paper could focus on the impact of the different types of Internet source use on total search effort.

A general question that still requires a definitive answer is why consumer search appears to be so limited, both in general and on the Internet. One possibility, which we are investigating for automobiles, is that consumers have sufficient prior information that they do not need to search (Moorthy, Ratchford, and Talukdar, 1997). In the case of the Internet, another possibility is that learning how to use different Web sites effectively is more costly than otherwise thought, giving familiar sites a lock-in advantage (Johnson et al., 2004). Another possibility is that a substantial proportion of Internet users have the high time costs, which is why they choose this medium in the first place. Alternatively, there may be psychological mechanisms that are not well understood at this point that serve to limit search both on the Internet and across sources in general (Johnson et al., 2004). Whatever the reason, the substantial degree of price dispersion observed both in Internet and traditional retail markets suggests that there are potential gains to further search. Consequently, it is difficult to explain why consumers do not appear to search much; this remains a fertile area for additional research.

## Notes

1. Representative examples of these studies of price dispersion are Brynjolfsson and Smith (2000), Baye, Morgan, and Scholten (2004), and Ratchford, Pan, and Shankar (2003).

2. An exception is when a consumer does not have access to a computer and would have to invest in a computer and learning how to use it in order to access the Internet. In this case we assume that $a_n$, the productivity parameter of the Internet as a source for that consumer, is zero.

3. Differentials in the enjoyment of using different sources could easily be modeled by assigning a different $w_j$ to each source. However, we have no data on the differential enjoyment of each source.

4. Corner solutions could result in some sources *i* being eliminated from Equation 2. However diminishing returns to information will assure that Equation 2 holds for at least one source and that time devoted to search is finite.

5. If a source *i* is not used, then $\partial F/\partial t_i < (w/g)e^{S+F}$ for all positive vales of $t_i$.

6. The standard logit model also has the same properties. Also, it can be shown that Cobb-Douglas production functions have these properties. The function $F$ in Equation 4 has the Cobb-Douglas form if all of the second order effects are 0.

7. We also collected a similar data set in February 2000, which was used in Ratchford, Lee, and Talukdar (2003), but is not used in this study because it does not contain the detailed information on use of different types of Internet sources that is the subject of the current study.

8. This alternative survey question, which was asked early in the survey well before the questions on the individual sources, was worded as follows: Approximately how much time did you *personally* spend gathering information before purchasing your *recent* new car? Consistent with past studies, cases where the alternative estimates of total time differed by more than 50 hours were discarded. There were only a few of these.

## References

Alba, Joseph, John Lynch, Barton Weitz, Chris Janiszewski, Richard Lutz, Alan Sawyer, and Stacy Wood. (1997) "Interactive Home Shopping: Consumer, Retailer and Manufacturer Incentives to Participate in Electronic Marketplaces." *Journal of Marketing,* 61 (3; July), 38–53.

Bakos, J. Yannis. (1997) "Reducing Buyer Search Costs: Implications for Electronic Marketplaces." *Management Science,* 43 (12; December), 1613–1630.

Baye, Michael, and J. Morgan. (2001) "Information Gatekeepers on the Internet and the Competitiveness of Homogeneous Product Markets." *American Economic Review,* 91 (3), 454–474.

Baye, Michael, John Morgan, and Patrick Scholten. (2004) "Temporal Price Dispersion: Evidence from an Online Consumer Electronics Market." *Journal of Interactive Marketing*, 18 (Autumn), 101–115.

Beatty, Sharon, and Scott Smith. (1987) "External Search Effort: An Investigation Across Several Categories." *Journal of Consumer Research,* 14 (June), 83–93.

Bettman, James, Mary Frances Luce, and John W. Payne. (1998) "Constructive Consumer Choice Processes." *Journal of Consumer Research,* 25 (December), 187–217.

Brown, J., and A. Goolsbee. (2002) "Does the Internet Make Markets More Competitive? Evidence from the Life Insurance Industry." *Journal of Political Economy,* 110 (3), 481–507.

Brynjolfsson, Eric, and Michael Smith. (2000) "Frictionless Commerce? A Comparison of Internet and Conventional Retailers." *Management Science,* 46(4), 563–585.

Bucklin, Randolph, and Catarino Sismeiro. (2003) "A Model of Web Site Browsing Behavior Estimated on Clickstream Data." *Journal of Marketing Research*, 40 (3), 249–267.

Claxton, John, Joseph Fry, and Bernard Portis. (1974) "A Taxonomy of Prepurchase Information Gathering Patterns." *Journal of Consumer Research,* 1 (December), 35–42.

Ellison, G., and S.F. Ellison. (2004) Search, Obfuscation and Price Elasticities on the Internet. Working paper, Sloan School of Management, MIT.

Erdem, Tulin, Michael P. Keane, and Judi Strebel. (2004) Learning About Computers: An Analysis of Information Search and Technology Choice. Working paper, University of California, Berkeley.

Furse, David, Girish Punj, and David W. Stewart. (1984) "A Typology of Individual Search Strategies Among Purchasers of New Automobiles." *Journal of Consumer Research,* 10 (March), 417–431.

Hauser, John, Glen Urban, and S. Weinberg. (1993) "How Consumers Allocate Their Time When Searching for Information." *Journal of Marketing Research,* 30, 452–466.

J.D. Power and Associates. (2002) *New Autoshopper.com Study.* Agoura Hills, CA.

Johnson, Eric, Wendy Moe, Peter Fader, Steven Bellman, and Gerald L. Lohse. (2004) "On the Depth and Dynamics of Online Search Behavior." *Management Science*, 50 (March), 299–308.

Kiel, Geoffrey, and Roger Layton. (1981) "Dimensions of Consumer Information Seeking Behavior." *Journal of Marketing Research,* 18 (May), 233–239.

Klein, Lisa, and Gary Ford. (2003) "Consumer Search and Information in the Digital Age." *Journal of Interactive Marketing,* 17 (Summer), 29–49.

Lal, Rajiv, and Miklos Sarvary. (1999) "When and How Is the Internet Likely to Decrease Price Competition?" *Marketing Science,* 18 (4), 485–503.

Lapersonne, Eric, Gilles Laurent, and Jean-Jacques Le Goff. (1995) "Consideration Sets of Size One: An Empirical Investigation of Automobile Purchases." *International Journal of Research in Marketing,* 12, 55–66.

Lynch, John, and Dan Ariely. (2000) "Wine Online: Search Costs Affect Competition on Price, Quality and Distribution." *Marketing Science,* 19 (Winter), 83–103.

Marmorstein, H., D. Grewal, and R. Fishe. (1992) "The Value of Time Spent in Price Comparison Shopping: Survey and Experimental Evidence." *Journal of Consumer Research,* 19 (June), 52–61.

Moe, Wendy, and Peter Fader. (2001) "Uncovering Patterns in Cybershopping." *California Management Review,* 43 (Summer), 106–117.

———. (2004) "Dynamic Conversion Behavior at E-Commerce Sites." *Management Science,* 50 (March), 326–335.

Moorthy, Sridhar, Brian T. Ratchford, and Debabrata Talukdar. (1997) "Consumer Information Search Revisited: Theory and Empirical Analysis." *Journal of Consumer Research,* 23 (March), 263–277.

Pan, Xing, Brian Ratchford, and V. Shankar. (2002), "Can Price Dispersion in Online Markets Be Explained by Differences in e-Tailer Service Quality?" *Journal of the Academy of Marketing Science,* 30 (4), 443–456.

Pan, Xing, Brain Ratchford, and V. Shankar. (2004) "Price Dispersion on the Internet: A Review and Directions for Future Research." *Journal of Interactive Marketing,* 18 (Autumn), 116–135.

Punj, Girish, and Richard Staelin. (1983) "A Model of Consumer Information Search Behavior for New Automobiles." *Journal of Consumer Research,* 10 (March), 366–380.

Ratchford, Brian. (1982) "Cost Benefit Models for Explaining Consumer Choice and Information Seeking Behavior." *Management Science,* 28 (2; February), 197-212.

Ratchford, Brian, Myung-Soo Lee, and Debabrata Talukdar. (2003) "The Impact of the Internet on Search for Automobiles." *Journal of Marketing Research,* 40 (May), 193–209.

Ratchford, Brian, and Narasimhan Srinivasan. (1993) "An Empirical Investigation of Returns to Search." *Marketing Science,* 12 (Winter), 73–87.

Ratchford, Brian, D. Talukdar, and M.S. Lee. (2001) "A Model of Consumer Choice of the Internet as an Information Source." *International Journal of Electronic Commerce,* 5 (Spring), 7–21.

Ratchford, Brian, Xing Pan, and V. Shankar. (2003) "On the Efficiency of Internet Markets for Consumer Goods." *Journal of Public Policy and Marketing,* 22 (1), 4–16.

Schmidt, Jeffrey B., and Richard A. Spreng. (1996) "A Proposed Model of Consumer Information Search." *Journal of the Academy of Marketing Science,* 24 (3), 246–256.

Scott Morton, Fiona, Florian Zettelmeyer, and Jorge Silva-Risso. (2001) "Internet Car Retailing," *Journal of Industrial Economics,* 49 (4), 501–520.

———. (2003) "Consumer Information and Discrimination: Does the Internet Affect the Pricing of New Cars to Women and Minorities?" *Quantitative Marketing and Economics,* 1 (March), 65–92.

———. (2004) How the Internet Lowers Prices: Evidence from Matched Survey and Auto Transaction Data. Working paper, University of California, Berkeley.

Srinivasan, N., and Brian T. Ratchford. (1991) "An Empirical Test of A Model of External Search for Automobiles." *Journal of Consumer Research,* 18 (September 1991), 233–242.

Strebel, Judi, Tulin Erdem, and Joffre Swait. (2004) "Consumer Search in High Technology Markets. Exploring the Use of Traditional Information Channels." *Journal of Consumer Psychology,* 14 (1 and 2), 96–104.

Westbrook, Robert, and Claes Fornell. (1979) "Patterns of Information Source Usage Among Durable Goods Buyers." *Journal of Marketing Research,* 16 (August), 303–312.

Wilkie, William, and Peter Dickson. (1985) *Shopping for Appliances–Consumers' Strategies and Patterns of Information Search*. Cambridge, MA: Marketing Science Institute.

CHAPTER 4

# CATEGORIZATION

## A Review and an Empirical Investigation of the Evaluation Formation Process

GINA L. MILLER, NARESH K. MALHOTRA, AND TRACEY M. KING

**Abstract**

*There is great need for a comprehensive, theoretically sound model of the product perception or evaluation formation process in the discipline of marketing. From a review of the categorization literature, a categorization-based model of the product evaluation formation process was developed, which assists in the prediction of set membership (i.e., evoked, inert, or inept). A summary of the theoretical background, as well as a description of the model is presented, and a research design is used to empirically test the category-based processing and piecemeal processing branches of the model. Through a survey of undergraduates, various methodologies were tested with regard to their abilities to predict set membership. The findings suggest that powerful tools exist for the prediction of set membership. Conclusions regarding the theoretical and methodological contributions of this study are drawn, and managerial implications of the findings, as well as recommendations for future research are discussed.*

A firm will gain a distinct advantage in the market if it is able to determine whether its product is included in a consumer's evoked set, and if not, where its product stands in relation to the evoked set. To assist in this task, researchers need to develop a model of the product evaluation formation process, because once this process is understood, it can be used to predict set membership. This model development and the demonstration of its subsequent power for set prediction (i.e., prediction of whether a product is contained in a consumer's evoked, inert, or inept set) are the main contributions of this chapter.

These goals are accomplished by first giving a brief overview of the evoked set concept and its relationship to categorization theory. Then, the literature on categorization theory is reviewed, which provides a theoretical framework for the product evaluation formation (EF) model. An empirical research design for testing the set prediction ability of the model is laid out in two parts: category-based processing and piecemeal processing. The procedures for carrying out the analyses of these two parts of the empirical investigation are outlined, and the results are discussed. Finally, conclusions are drawn, contributions made by the study are highlighted, and recommendations for future research are identified.

## Categorization Literature Review

The categorization approach to information processing posits that consumers store information in memory around a set of category expectations (Rosch, 1975; Rosch and Mervis, 1975; Rosch et al., 1976). Categorization itself involves the comparison of a marketing stimulus (e.g., brand or product) with knowledge stored in memory (see Basu, 1993). A consumer's knowledge store is comprised of a variety of groups, or "sets," of brands. The evoked set can be thought of as a subset of the awareness set—the brands a consumer is aware of or expects to be a member of a certain category. Once a consumer is aware of a brand, it can fall into one of three subsets: the inert set, the inept set, or the evoked set. The *inert set* is comprised of those brands for which the buyer has a neutral evaluation (i.e., he does not think positively or negatively about them). This may be because he does not have sufficient information to make such a judgment or because he has no reason to try them. The brands that have been rejected by the consumer, owing to such factors as a bad experience with the brand or exposure to negative information, make up the *inept set*. The *evoked set* is then the set of brands that the consumer evaluates positively and considers for purchase. In order to simplify their decision-making processes, consumers categorize the brands available in the marketplace into one of these three sets (Narayana and Markin, 1975; see also Brown and Wildt, 1991; Nedungadi, 1990; Turley and LeBlanc, 1995). When faced with a choice, consumers recall from memory the products that would fulfill their needs in a positive manner (the evoked set) and make their final choice from this set (Ratneshwar and Shocker, 1991). If a product is not included in the consumer's evoked set, then it will not be chosen.

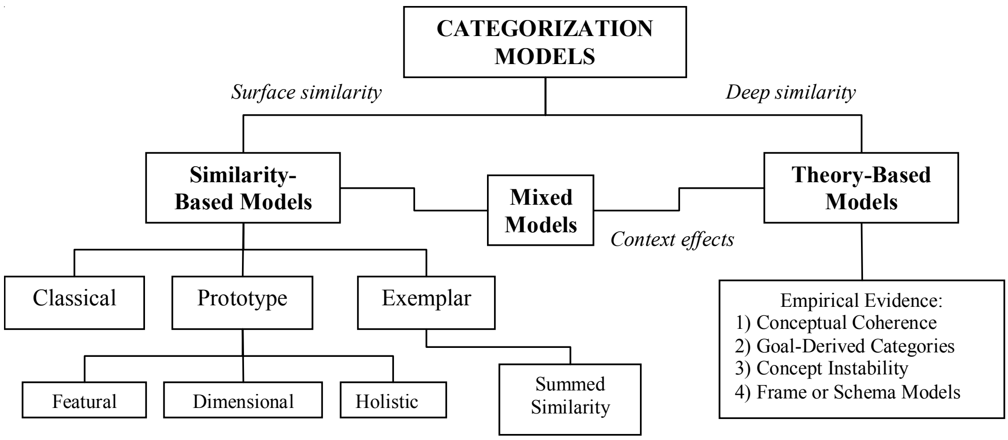
This realization holds considerable implications for the application of categorization theory to product evaluations, since understanding how consumers categorize or make product evaluations would be invaluable to marketers. In other words, "Categorization theory is particularly relevant to understanding consumer behavior because consumers face a complex choice environment replete with brands having both shared and unique features; consumers may use categorization to simplify and structure their environment" (Sujan and Tybout, 1988, p. 50). In fact, in recent years consumer researchers have investigated a variety of issues in product categorization—for example, consumers' mental representations of product categories (e.g., Loken and Ward, 1990; Ratneshwar and Shocker, 1991; Sujan and Bettman, 1989), the relation between categorization and consideration sets (e.g., Hutchinson, Raman, and Mantrala, 1994; Nedungadi, 1990; Ratneshwar, Pechmann, and Shocker, 1996; Ratneshwar and Shocker, 1991), and how categorization affects consumers' preferences and choices (e.g., Goodstein, 1993; Meyers-Levy and Tybout, 1989; Stayman, Alden, and Smith, 1992; Sujan, 1985). Basically, a strong understanding of categorization theory assists in making accurate predictions regarding how consumers interpret and respond to marketing stimuli (Sujan and Dekleva, 1987; Sujan and Tybout, 1988).

It is essential to review the categorization literature when conducting any type of information processing research since the grouping of similar concepts (i.e., categorization) results in enhanced information processing efficiency and cognitive stability (Cohen and Basu, 1987; Corter and Gluck, 1992; Ozanne, Brucks, and Grewal, 1992). For the purposes of this chapter, two main classes of categorization models are examined: similarity-based models and theory-based models. Then a third type, known as mixed models, is discussed in an effort to integrate the two previously mentioned classes of models (see Figure 4.1).

### *Similarity-Based Categorization Models*

Most theoretical accounts of categorization are built around the assumption that similar objects are grouped together; thus, similarity is often assumed to be the primary determinant of category

Figure 4.1 **Categorization Models**




representations (Murphy and Medin, 1985; Rosch and Mervis, 1975; Smith and Medin, 1981). Similarity-based models take a bottom-up or stimulus-based view of categorization where the perception of salient features of stimuli is critical in determining category membership (Ratneshwar et al., 2001). The three most commonly employed similarity-based models of the categorization process are the classical view, the prototype view, and the exemplar view (Medin and Smith, 1984; Smith and Medin, 1981).

*Classical View*

The classical view is based on two assumptions. The first is that "the representation of a concept is a summary description of an entire class, rather than a set of descriptions of various subsets or exemplars of that class." Second, "the features that represent a concept are singly necessary and jointly sufficient to define that concept. For a feature to be singly necessary, every instance of the concept must have it; for a set of features to be jointly sufficient, every entity having that set must be an instance of the concept" (Smith and Medin, 1981, p. 23). These assumptions imply that all category members are equally representative of the category, and that category membership is an "all or nothing" prospect. In other words, if a given concept lacks even one of the critical features of a category, it cannot be a member of that category. If this nonconformatory situation exists, one of two things must occur: the set of critical features for the category must be modified or the concept must be placed in another, possibly new, category. Since many thought this view too restrictive, the idea that concept representations are based on properties that are only characteristic or typical of category exemplars evolved, which is known as the probabilistic view. This shift is considered to be the first of two major shifts that have occurred in categorization theory and is illustrated by the prototype view (Medin and Coley, 1998).

*Prototype View*

The prototype view may be described by the following: "The representation of a concept is a summary description of an entire class; and the representation of a concept can not be restricted to a set of necessary and sufficient conditions; rather, it is some sort of measure of central tendency of the instances' properties or patterns" (Smith and Medin, 1981, p. 61). In other words, prototype models assume that the stored category representation is a summary of the most typical feature values for members of a category, and that new stimuli are classified on the basis of their similarities to these prototypes (Hampton, 1995). The relevant literature encompasses three different representations of a prototype: featural, dimensional, and holistic.

*Featural Approach.* The critical assumption of the featural approach is that "the features that represent a concept are salient ones that have a substantial probability of occurring in instances of the concept" (Smith and Medin, 1981, p. 62). Under this approach, each feature associated with a category is accompanied by a weight that reflects the saliency of the feature, thus making this an analytical approach. For example, features such as "feathered" and "winged" would have high weights for the concept of bird, since they always occur on category members. Less prevalent, or salient, features such as "flies" and "sings" would have lower weights.

*Dimensional Approach.* The dimensional approach is also analytical, and its critical assumption is that "any dimension used to represent a concept must be a salient one, some of whose values have a substantial probability of occurring in instances of the concept; and the value of a dimension represented in a concept is the (subjective) average of the values of the concept's subsets or instances on this dimension" (Smith and Medin, 1981, p. 103). Thus, dimensions are assigned weights, as in the featural approach. The main distinction between this approach and the featural approach is that the dimensions can be physically or psychologically continuous (i.e., size)—they do not have to be discrete (i.e., winged) as in the featural approach.

*Holistic Approach.* The third and final approach is the holistic one, which is nonanalytic. In this case, a prototypical concept is represented by a single overall representation of the concept. Smith and Medin (1981) treat the holistic approach as a template theory. A template is isomorphic—it looks like the object it represents (i.e., it is similar to a picture of the object). For example, if the concept of cup was represented in template form, the feature "has a handle" could not be singled out and analyzed alone, since the handle is incorporated into the isomorphic representation of the cup; however, the relationship between the handle and the cup would be apparent. In the featural or dimensional approach, "has a handle" would be separable from the overall concept of cup, but the relationship between the handle and the cup would not be inherently apparent (Smith and Medin, 1981).

In spite of, or perhaps because of, the three approaches to prototype theory, the nature of a prototype is vague. Furthermore, the prototype view has a number of limitations. One flaw involves prototype theory's requirement of an abstract, summary representation. It does not explicitly provide for the incorporation of new information about a concept. In other words, it is unclear "how the new information is to be combined with it [the prototype] (e.g., some complex type of weighting scheme) depending on various characteristics of the already existing prototype" (Cohen and Basu, 1987, p. 460). Also, central tendency notions claiming the prototype as an "average" do not explain the systematic biasing effects that have been empirically demonstrated in categorization literature (e.g., Cohen and Basu, 1987). Furthermore, Medin (1989) notes that prototype theory treats concepts as context-independent entities and does not account for goal-derived categories, which are based on similarity to an ideal rather than to a prototype (Medin, 1989).

*Extension of Prototype View.* Rule-bound (decision-bound) models are extensions of the prototype model of categorization. Rule-based models posit that decisions are based on abstracted rules. The rule is derived using a decision bound (e.g., a line or curve) to divide the relevant psychological space, and the resulting regions are each assigned to a specific category (e.g., Ashby and Gott, 1988; Ashby and Maddox, 1990, 1992, 1993). For example, a person might be categorized as "tall" if he or she is perceived as exceeding 6 feet (Rouder and Ratcliff, 2004). In recent years, rule-based theories have been integrated with the exemplar view to produce dual-process or dual-system categorization models (e.g., RULEX; Nosofsky et al., 1994; Nosofsky and Palmeri, 1998), which are discussed after an introduction to the exemplar view of categorization.

*Exemplar View*

In the exemplar view, concepts are represented by specific category exemplars rather than by an abstract summary (Kruschke, 1992; Nosofsky, 1986; Palmeri and Nosofsky, 1995; Smith and Medin, 1981). Thus, "the more similar the target instance is to concrete exemplars of a category, the more likely it will be placed in that category" (Cohen and Basu, 1987, p.460). The exemplars, which have been previously encountered and stored in memory, retrieved for comparison to the target, will be ones that are contextually relevant (Yang and Lewandowsky, 2003). This indicates that in categorization instances where the concepts are influenced by the context, the exemplar model will predict categorization results more accurately than prototype models. An exception would occur if one assumes that for each specific situation, separate categories with individual prototypes are created. However, this exception is not very likely due to the fact that it would result in a large number of categories and undermine the efficiency of the cognitive system. In addition, the presence of a large number of categories would violate Rosch's (1975) two competing principles for determining the optimal level of categorization: minimization of the number of categories and maximization of informativeness.

The basic difference between exemplar and prototype theories may be explained by the nature of representational points in the category. Exemplar theory predicts that humans store a variety of exemplars in memory that are spread out in psychological space and act as the standards of comparison for new stimuli. Taking this perspective, each stimulus that is categorized will be like some exemplars and unlike other exemplars. On the other hand, prototype theory predicts that humans store one representational point at the center of the psychological space and that this prototype becomes the standard of comparison for new stimuli. Thus, stimuli that are categorized using the prototype model will be either like or unlike the one prototype. Smith (2002) conducted a study to test the appropriateness of exemplar theory using the predictions described above (see also Nosofsky and Johansen, 2000; Smith and Minda, 2000, 2002). Specifically, he determined whether or not there was a steep typicality gradient leading up to the prototype, as predicted by prototype theory (i.e., members of categories represented by prototypes will be either marginal or exceptional examples), or if there was not a steep typicality gradient, as predicted by exemplar theory (i.e., members of categories represented by exemplars will all be about equally good examples). The results show that while prototype theory's prediction was clearly supported, exemplar theory's prediction was not. However, exemplar models have been found to outperform prototype models in other empirical comparisons (Ashby and Maddox, 1998; Niedrich, Sharma, and Wedell, 2001). As discussed in a recent article by Minda and Smith (2001), individuals may be more likely to follow the prototype model of categorization when they are not very familiar with specific exemplars or when the stimuli are complex. These results support a mixed models approach, which is similar to the convergence of rule-based and exemplar-based strategies as discussed in the following section.

*Extension of Exemplar View.* A stream of literature by Nosofsky (Nosofsky, 1986, 1988a, 1989; Nosofsky, Shin, and Clark, 1989; based on the groundwork previously laid by Estes, 1986; Medin and Schaffer, 1978) attempts to justify the exemplar-based model empirically via a "summed similarity" approach. Nosofsky's work is primarily aimed at refuting the claims that the exemplar model is not a valid one, since high recognition does not necessarily lead to high categorization. He argues that the exemplar model consistently fits empirical data when a summed similarity approach is used.

The key assumption of the summed similarity approach is that categorization is determined by the relative degree of target-category to contrast-category similarity; whereas recognition, or familiarity, may be determined by the overall summed similarity of a probe to all exemplars stored in memory. For this reason, categorization and recognition may often be based on common representational substrates, but different decision rules may underlie performance in each task:

*Categorization Probability:*

$$P\left(R_j \mid S_i\right) = \frac{\Sigma N_j s_{ij}}{\Sigma\left(\Sigma N_k s_{ik}\right)}$$

*Recognition:*

$$F_i = \Sigma\left(\Sigma N_k s_{ik}\right)$$

where the probability that stimulus *i* is categorized in category *j*, is found by summing the similarity of stimulus i to all exemplars j belonging to category j and then dividing by the summed similarity of stimulus *i* to all exemplars of all categories, *k*. $P(R_j|S_i)$ is a measure of the "strength" of making a Category J response $(R_j)$ given the presentation of Stimulus $i$ $(S_i)$. *N* represents the relative frequency of exemplar *j*, and *s* represents the similarity between exemplars *i* and *j* or *k*. Recognition or familiarity is given by *F* (Nosofsky, 1988a).

The above model is expanded on in a paper by Nosofsky, Shin, and Clark (1989), which employs the assumption that similarities among exemplars are modifiable by selective attention. Selective attention is represented in terms of stretching and shrinking distances in psychological space. Each exemplar is thought of as a point in psychological space, and the difference between the coordinates of the points of two exemplars is used to calculate psychological distance. This distance is then converted to a similarity measure, so that the similarity between two exemplars can be determined. The selective attention exemplar model may "represent a compromise, in which specific experiences are stored; but with attention focused on those aspects of exemplars that appear most relevant to categorization" (Nosofsky, Shin, and Clark, 1989, p. 300).

Recently, a number of researchers have proposed multiple-process or multiple-system frameworks, where both exemplar- and rule-based processing are assumed to occur under the same model (e.g., Ashby and Ell, 2002; Erickson and Kruschke, 1998; Nosofsky, Palmeri, and McKinley, 1994; Vandierendock, 1995). According to these models, people identify rules that accurately predict the classification of most objects; however, these rules are augmented by the storage of a set of exceptions or unique feature combinations. Thus, if the use of a rule-based strategy fails or produces an unacceptable amount of errors, then people may retrieve one of a number of exceptions stored in memory. Nosofsky and colleagues' rule-plus-exception model (RULEX) is one example of this type of model and accounts for a categorization process that uses both rules and stored exemplars (Nosofsky, Palmeri, and McKinley, 1994; Nosofsky and Palmeri, 1998). The model is supported by Rouder and Ratcliff (2004) in a study that shows how both rule-based and exemplar-based processing may be used in the same categorization task. More specifically, exemplars were used in easy tasks involving no stimulus confusion, whereas rules were used in more difficult tasks where simplification was needed.

*Similarity-Based Category Structure*

In addition to examining how categories are learned and used, internal categorical structure is also discussed. The way that a category is structured has important implications for its usefulness in information search situations, classification, and judgment and choice tasks. Categorical structure for similarity-based models can be examined from two angles: the level of generality of the category and the graded structure within the category.

*Levels.* There are three levels of generality at which a category may exist: basic, subordinate, and superordinate. The *basic level* is where within-category similarity is maximized relative to between-category similarity, and the level at which objects are spontaneously named. In addition, basic-level categories are the most informative and the most useful for communication (Corter and Gluck, 1992). As an example, soft drinks might be considered a basic-level category. *Subordinate categorization* is the "ability to categorize below the basic level . . . [and it permits] finer discriminations to be made with greater reliability" (Alba and Hutchinson, 1987, p. 415). Thus, orange-flavored soft drinks would be a subordinate level category. *Superordinate categorization* is categorization above the basic level and tends to be more qualitative and abstract. Therefore, the concept of beverage would be the superordinate category for soft drinks. The ability to categorize at different levels allows the consumer to make choices more easily and in a more satisfactory manner.

At this point, it is important to discuss the basic level, and why it is considered an essential concept to categorization theory. As stated earlier, spontaneous categorization tends to occur at the basic level (Corter and Gluck, 1992; Mervis and Crisafi, 1982; Mervis and Rosch, 1981; Murphy and Brownell, 1985; Rosch et al., 1976) and is faster than at the subordinate or superordinate level. Murphy and Brownell (1985) investigated why the basic-level possesses these qualities. They suggest that faster categorization at the basic level occurs due to one of two factors: the shorter and more frequent names of basic categories (Corter and Gluck, 1992; Mervis and Crisafi, 1982), which are learned earlier in life (i.e., the preferred level hypothesis), and the fact that basic categories are more highly differentiated than other categories (i.e., the differentiation hypothesis).

The second factor, the differentiation hypothesis, is the theory that Murphy and Brownell (1985) advocate. It is comprised of two components: specificity and distinctiveness. Specificity is, in essence, informativeness. As one moves from the superordinate through the basic to the subordinate level, specificity increases. Distinctiveness takes into account how dissimilar a category is to its contrast categories. Therefore, as one moves from the subordinate to the superordinate level, distinctiveness increases. Upon consideration of these two components, one comes to the realization that they act in opposition to one another. Although this might seem to discount the plausibility of this theory, it in fact does just the opposite. It offers an explanation for why categorization may occur faster at the basic level than at other levels. While superordinate categories have maximum distinctiveness, they have the lowest specificity. Subordinate categories have maximum specificity but low distinctiveness. Basic categories have intermediate levels of both components; therefore, they possess more overall differentiation (Murphy and Brownell, 1985).

As Medin, Lynch, and Solomon (2000, p. 131) point out in their recent literature review, there is much research that supports a "blurring of the distinction between [category] levels" and "undermines the notion that basic-level concepts are special kinds of concepts that reflect the structure of the world, independent of knowledge, expectations, goals, and experience." First, it may be that one's "basic level" changes as a function of expertise (e.g., Johnson and Mervis, 1997, 1998; Tanaka and Taylor, 1991). For example, Mandler et al. (1991) conducted research to support Rosch et al.'s (1976) claim that children learn superordinate categories before learning basic-level categories, which suggests that superordinate categories may be considered more "basic" at a low level of experience. In addition, research shows that experts may prefer to name categories at the subordinate level over the basic level, and that they name each equally fast. It has been suggested that an increase in expertise simply allows one to be able to attend to different and more subtle perceptual features, which results in subordinate categories functioning as basic-level categories, but does not involve an overall shift to more abstract conceptual bases for categorization (Johnson and Mervis, 1997).

*Prototypicality.* Graded structure within categories is the second aspect of similarity based categorical structure that is discussed. It is "a continuum of category membership, ranging from prototypical members through unclear cases to prototypical nonmembers" (Barsalou, 1983, p. 211). Thus, category membership is a matter of degree. In the consumer behavior literature, researchers argue that brands exhibit graded structure as they vary in terms of being highly representative or typical of a brand category to being highly unrepresentative or atypical (Boush, 1993; Boush and Loken, 1991; Viswanathan and Childers, 1999). For example, consumers are likely to perceive a TV set as more representative of the Sony brand than a pair of shoes (Boush and Loken, 1991). As the protypicality of a brand or product increases, probability of its inclusion in the consumer's evoked set, chance of correct categorical classification, use as a standard of comparison, and level of evaluation are also assumed to increase (Loken and Ward, 1990).

Under the prototype and exemplar models, graded structure is determined primarily by similarity and frequency; for example, familiar exemplars are judged to be more typical than unfamiliar ones (see Loken and Ward, 1990). Nosofsky (1988b) found that high frequency exemplars and exemplars similar to the high frequency exemplars experienced increased classification accuracy and typicality ratings. Furthermore, similarity and frequency can influence one another. This is especially true in the event that selective attention occurs (Nosofsky, Shin, and Clark, 1989). Increased frequency may lead to selective attention and thus modify similarity relations. Use of a "representativeness" heuristic, the notion that people estimate the probability of an event by how similar it is to essential characteristics of the population, can cause people to ignore base rates (i.e., frequency).

### *Theory-Based Categorization Models*

All of the traditional models of categorization discussed above (i.e., classical, prototype, and exemplar models) assume that similarity plays the critical role in categorization (Ahn and Medin, 1992). These models espouse the belief that cognitive classification maximizes within-category similarity relative to between-category similarity. Although this idea is not without merit, it is not sufficient to explain categorization—especially since it forces one to ask, in the words of Medin (1989, p. 1473), "Do things belong in the same category because they are similar, or do they seem similar because they are in the same category?"

Although similarity assessments often lead to efficient and accurate categorization processes, a number of researchers suggest that the "theories" people have about the world may also drive categorization processes (Gopnik and Meltzoff, 1997; Keil, 1989; Murphy and Medin, 1985).

For the purposes of this chapter, a theory can be loosely defined as "the causal knowledge that people use to infer nonobvious properties and to explain observed patterns in the world" (Markman and Gentner, 2001, p. 231). This view leads to what is considered to be the second shift in recent categorization theory—the shift to theory-based or knowledge-based models.

*Foundations of Theory-Based Models*

Similarity-based models have been criticized mainly for ignoring the role of theories, which helps to explain why salient features may or may not be essential in determining category membership (Goldstone, 1994; Murphy and Medin, 1985). Several specific problems with similarity can be identified. First, similarity is too flexible or unconstrained. If categorization is presumed to occur through the matching of a list of features or attributes on the basis of similarity, then one must realize that these lists are a biased sample of an individual's knowledge. Thus, without constraints on what may be considered a feature, objects/alternatives could be arbitrarily similar or dissimilar.

A second problem with similarity is the fact that most concepts/objects possess a structure; that is, they are not a simple sum of independent features (Wattenmaker, 1993). Both attributes and relations are necessary for structure, since the relations serve to bind the attributes together in a meaningful way. Therefore, categorization may be more like a general form of decision making rather than just simple attribute matching. This leads to the conjecture that real-world knowledge is used to reason about or explain properties, not simply to match them.

Therefore, one can arrive at the conclusion that rather than being a cause of conceptual coherence, similarity may be a by-product. If categories were theory based, each object to be classified would have to have the correct "explanatory relationship" to the theory or idea that was responsible for organizing the concept. Consequently, this view begins to offer some insight into why individuals have the categories that they do, which includes categories that contain items that have no obvious source of similarity. This is related to the argument that similarity-based models have no way of explaining whether or not different sets of items will be retrieved, or perceived as similar, under different situations. In other words, they do not account for the influence of context on category membership.

Although theory based-categorization is important, scholars should remain cautious about simply ignoring the importance of feature-based similarity. In fact, researchers have proposed a similarity calculation that is based on a structural alignment process, which allows for the inclusion of both features and relations to determine the level of similarity between stimuli (e.g., Goldstone, 1994; Gentner and Medina, 1998). Medin (1989) suggests that similarity-based categorization should be modified and linked with theory-based categorization. He proposes the following key tenets:

(a) Similarity needs to include attributes, relations, and higher-order relations.
(b) Properties in general are not independent but rather are linked by a variety of interproperty relations.
(c) Properties exist at multiple levels of abstraction.
(d) Concepts are more than lists; properties and relations create depth or structure (Medin, 1989, p. 1476).

According to Medin (1989; Medin and Ortony, 1989), one way that similarity is linked to theory-based categorization is through psychological essentialism—the idea that people behave as if things have underlying natures that make them the things they are. Theories then provide causal linkages from deeper properties to more superficial or surface properties. In addition, people adopt what he refers to as the essentialist heuristic—things that look alike tend to share deeper properties or similarities. Interestingly, this heuristic is often correct. Thus, classifying objects on the basis of featural similarity will be effective most of the time and will give knowledge of deeper principles regarding the object. For instance, structure is often correlated with function. It should be noted that this idea is somewhat of a forerunner to the two-stage or "first-cut" model presented in the mixed models section of this chapter.

### *Theory-Based Category Structure*

As with similarity-based categories, the structure of theory-based categories is also examined. The way that theory-based categories are structured is especially important in understanding the processes leading to knowledge transfer between existing categories and novel stimuli.

*Levels.* Like similarity-based models, theory-based models contain different levels within their category structures. However, unlike similarity-based models, these levels are not well defined, and no one view is endorsed by a consensus of researchers. Three main approaches for examining the structure of theory-based models exist. All of these views incorporate the word "similarity" into their terminology, but here the term is used to refer to both featural similarity and relational or functional similarity.

First, theory-based categorization models can be examined using two levels where similarity may refer to either *surface similarity* or *deep similarity.* Surface similarity was originally defined as perceptual or featural level similarity, which is similarity derived from sensory systems, such as vision. However, Vosniadou (1989) argues that surface similarity should be termed *salient similarity* and should incorporate both featural and functional similarity, provided that the similarity in question encompasses relevant and easily retrievable aspects of the object to be categorized. On the other hand, deep or relational similarity deals with the idea that objects can be similar owing to the fact that they perform analogous functions or are functionally interrelated—in that they are dependent upon each other in some way. This approach asserts that concepts have, and are related by, an underlying structure that is deeper than surface or featural similarity (Barr and Caplan, 1987).

A second approach, advocated particularly by L. Smith (1989), also consists of two levels. In this case, the levels are known as *global* and *dimensional* similarity. Global similarity is in essence holistic similarity, the similarity of the whole object to the representation of the category. Dimensional similarity is just what its name suggests. It implies that objects to be categorized can be compared along discriminable dimensions instead of as a whole. Furthermore, as in the previous method, the two levels are not mutually exclusive, since a single object can be viewed and evaluated from the perspective of both levels.

Analogical reasoning provides the basis for the final approach (Gentner, 1983, 1989; Goldstone, Medin, and Gentner, 1991; Medin, Goldstone, and Gentner, 1993; Wattenmaker, 1993). Analogical reasoning involves the transfer of information from one domain (base or source domain) to another domain (target domain) that is perceived to be similar on some level. The critical assumption behind analogical reasoning is the idea that domains related in some respects are likely to be related in other respects as well (Gregan-Paxton and John, 1997). Analogical reasoning can serve to build "bridges" across which information between objects or domains can be transferred. Recent research shows that consumers may use information from multiple relevant and accessible categories to learn and make inferences about novel objects (Moreau, Markman, and Lehmann, 2001).

In consumer behavior literature, knowledge transfer has been studied in multiple contexts including brand extension evaluations (e.g., Aaker and Keller, 1990; Boush and Loken, 1991; Broniarczyk and Alba, 1994; Park, Milberg, and Lawson, 1991), country-of-origin effects (e.g., Hong and Wyer, 1989, 1990; Shimp, Samiee, and Madden, 1993), and comparative advertising (e.g., Pechmann and Ratneshwar, 1991; Snyder, 1992; Sujan and Dekleva, 1987). The knowledge from a familiar domain (e.g., an existing category) is transferred to an unfamiliar target in three stages: access, mapping, and transfer (Gentner, 1989; Gregan-Paxton and John, 1997; Holyoak and Thagard, 1989; Markman and Wisniewski, 1997). The notion of categorization-based knowledge transfer is especially applicable to research on new product perception, where a novel item is classified as a member of an existing product category, and information in that category is transferred to the novel item and used to structure the new representation (Moreau, Markman, and Lehmann, 2001). This process occurs via four types of comparisons or levels: mere appearance matches, literal similarities, analogies, and applications of abstractions.

Mere appearance matches possess a strong overlap in object-attributes (surface similarity), but no overlap in relations (deep similarity). For example, the statement "a caret is an inverted 'v'" has no deeper meaning, only featural similarity. For this reason, mere appearance matches are not very informative. Mere appearance matches are also particularly prone to errors in the transfer process since comparisons are based entirely on attribute overlap (Gregan-Paxton and John, 1997). Literal similarities include the transfer of both object-attributes and relations. However, the number of object-attributes mapped is much greater in proportion to the number of relations mapped from the base to target domain. "Milk is like water" is an example of this type of comparison. Milk and water have many perceptual similarities (i.e., they are both liquids and wet), but only some relational similarities (i.e., both can be consumed) (Gentner, 1989).

Analogies (i.e., relational comparisons) are comparisons where relations are mapped, but few or no object-attributes are transferred between domains. For example, "The hydrogen atom is like the earth's solar system." The nucleus of the atom is not really perceptually similar to the sun (i.e., it is not yellow), but more importantly, it is relationally similar (i.e., electrons revolve around the nucleus as the planets revolve around the sun). Abstractions are special cases of analogies in that only relational similarities are mapped and object-attributes are not, and the mapping occurs from a base domain that is an abstract relational structure—for example, "The hydrogen atom is a central force system." From the abstract base domain (central force system), one can know that the central/more massive object attracts the peripheral/less massive object. From this, one can then infer that the nucleus must attract the electron, and the electron must revolve around the nucleus (Gentner, 1983).

*Prototypicality.* Like similarity-based categories, theory-based categories also exhibit graded structure or prototypicality. The difference between the two types of categories links to the notion of family resemblance (Rosch and Mervis, 1975), where family resemblance states that good category examples are highly similar to other category members and highly dissimilar to members of other categories. Natural categories (in both similarity-based and theory-based models) exhibit family resemblance, whereas ad hoc categories (accounted for in theory-based models) do not. For example, in the natural category "things to sit on," the category member of wooden chair would be highly similar to other members (i.e., stool, sofa). However in the ad hoc category "things to prop doors open with," a chair might be a category member, and so might a rock—yet no family resemblance between these two category members exists. Therefore, although prototypicality is determined by "ideals" for both natural and ad hoc categories, family resemblance is used to establish prototypicality only for natural categories and not ad hoc categories (Alba and Hutchinson, 1987).

*Empirical Evidence: In Support of a Theory-Based View*

One of the main functions theory-based categorization models perform is that they allow for the incorporation of contextual and typicality effects, which have been shown numerous times in the literature (e.g., Barsalou, 1982, 1985, 1987, 1989; Medin and Shoben, 1988). Empirical testing of various contextual and typicality (i.e., graded structure) effects are found in the areas of conceptual coherence, goal-derived categories, concept instability, and frame/schema models.

*Conceptual Coherence.* The argument for theory-based categorization is further strengthened by the experimental results of Medin and Shoben (1988), which demonstrate that theories can affect judgments of similarity via consideration of the theories themselves or their explanation of the underlying functional relationships between objects (see also Murphy and Medin, 1985; Smith et al., 1988). For example, individuals tend to perceive the concepts of gray and black as more similar to each other than to white when paired with "cloud"; however, white and gray are judged to be more similar to each other than to black when paired with "hair." These results may be construed as evidence that in the first instance, gray and black are related via a "storm" theory, and in the second instance, white and gray are linked through an "aging" theory (Medin and Shoben, 1988). Thus, contextual effects, such as the wording of alternatives in a decision or categorization situation, can be accounted for by theory-based categorization. In addition, the results suggest the notion of property centrality—the same property may be equally true of two different concepts but may be more central to one concept through its role in the internal structure of that concept. For example, being round is a property of a basketball and a cantaloupe; however, roundness is a more central aspect of a basketball, since it is essential to the function of a basketball (Medin and Shoben, 1988).

*Goal-Derived Categories.* Nontaxonomic categories are very important because many categories that are used by consumers are nontaxonomic or goal related. This view of categories suggests that objects are grouped together, or are perceived to be similar, if they share a set of associations in memory that are organized around common goals (e.g., Austin and Vancouver, 1996; Barsalou, 1983, 1985; Huffman and Houston, 1993). In consumer behavior research, goals are construed at the level of benefits the consumer seeks from a particular product, service, or consumption experience (see Huffman and Houston, 1993; Ratneshwar, Pechmann, and Shocker, 1996). For example, an individual on a diet may construct a "breakfast" category consisting of products such as an apple, a granola bar, and yogurt, along with other seemingly diverse, but all healthy, foods. A recent study by Ratneshwar et al. (2001) illustrates that consumers' similarity judgments of products were influenced not only by salient, surface-level features but also by product benefits related to salient personal *and* situational goals. Thus, both individual and situational differences in goal salience must be considered when explaining category representations (see Ratneshwar, Pechmann, and Shocker, 1996).

The extent to which categories are goal related is probably best exemplified by Barsalou's (1983, 1991) work in ad hoc categories. Ad hoc categories are a subset of goal-derived categories (Alba and Hutchinson, 1987; Ratneshwar and Shocker, 1991; Ross and Murphy, 1999). They are created spontaneously for use in specialized contexts or in infrequently encountered situations.

Ad hoc categories are further differentiated by the fact that category members are not necessarily highly similar to each other; rather, category membership requires that they possess a set of shared goal-related attributes (Barsalou, 1983). For example, an infrequent flier may be unable to easily recall food to eat when in a hurry at an airport. Rather than simply recalling a well-established set of category members, he or she will spontaneously create a new ad hoc category. This is done by first considering issues related to the particular situation (e.g., little time before flight departure; overpriced food) and then one's situational goals (e.g., quick but cheap food; see Desai and Hoyer, 2000; Huffman and Houston, 1993). This notion of ad hoc categories serves as additional evidence to support the theory-based view of categorization.

*Concept Instability.* Concept instability occurs as a result of contextual effects. This is because, in Barsalou's (1982) terminology, concepts contain context-independent and context-dependent information. Context-independent information is information tied to the core meaning of the concept—information inherently associated with the concept and always activated, regardless of the context. For example, Barsalou (1989) points out that when the concept "frog" is activated, information such as "green" and "hops" comes to mind for most people. In a marketing context, whenever a person thinks of certain brands, he may spontaneously recall certain qualities that he associates with the brand (Desai and Hoyer, 1993). For example, one may immediately think of "reliability" and "good quality" when the brand Honda is brought to mind. This information is then context-independent information. Context-dependent information, on the other hand, is information that is retrieved only when it is relevant to the concept in the current context. For example, in the context of French restaurants, the previously mentioned concept of "frog" retrieves context-dependent information like "eaten by humans." Similarly, qualities such as "power" and "adrenaline rush" may be retrieved when one thinks of a Honda motorbike, but not necessarily when one thinks of a Honda car.

From the above example, it can be seen that the information retrieved for a given concept in a given situation (i.e., the concept representation) may differ from occasion to occasion and from person to person. Therefore, a concept's representation and graded structure (Barsalou, 1985) may change with context and are thus unstable. In other words, since the same concept may be represented in more than one way, several representations of a single concept exist in memory and share similarities. It follows then that representations for two different concepts may be unrelated or similar, depending on the particular context (Barsalou, 1987). Concepts can be viewed as complex, interrelated, and dynamic entities that are constructed in working memory as the occasion demands. Furthermore, it can be seen that a very flexible and complex model would be required to account for this idea. The theory-based models do this nicely, and one particularly appropriate interpretation of how this might occur cognitively is exemplified by Barsalou's (1992) frame theory of categorization.

*Frame or Schema Models.* Frame or schema models are widely dispersed throughout the cognitive literature (e.g., Barsalou, 1992; Brewer and Nakamura, 1984; Rumelhart, 1984). More importantly, theory-based categorization provides for the idea that concepts/schemas/frames that integrate attributes in dynamic relational structures can be constructed "on the fly" (i.e., as they are needed by the individual). This is because the individual maintains a base of theories or knowledge to draw from in order to create new concepts as the occasion demands.

Barsalou (1992, p. 21) proposes that "frames provide the fundamental organization of human knowledge." Frames possess three components: attribute-value sets, relations between attributes, and constraints. In attribute-value sets, attributes, values, and concepts are all related in the sense that a concept can be a concept, an attribute, or a value, depending on the situation. When a concept describes an aspect of a large whole, it is an attribute. For instance, a favorite color is a concept, whereas the color of a bird is an attribute. On the other hand, "values are subordinate concepts of an attribute" (Barsalou, 1992, p. 31). Therefore, values contain the properties of the attribute with which they are associated. If eight-cylinder is a value for the attribute engine, it includes the properties of an engine. Values can also be attributes. If one is discussing whether the eight-cylinder engine is a straight eight or a V-8, eight-cylinder can be viewed as an attribute, and straight eight and V-8 are values associated with it.

The third component of frames, constraints, brings into play the idea previously put forth that attributes are not independent of one another. The various values "constrain each other in powerful and complex manners" (Barsalou, 1992, p. 37). For example, a consumer may store in memory the constraint that, since he has a long commute to work everyday, he requires a fuel-efficient car with comfortable seats, and that compact cars best meet these requirements (see Ratneshwar, Pechmann, and Shocker, 1996).

### *Mixed Models: Moving Toward an Integration*

Perhaps the best way to arrive at an integration of the traditional models and the theory-based models is to realize that, in a very broad and general sense, both types of models are goal oriented. This statement means that the overriding purpose of categorization is to achieve the goal of cognitive organization. In the traditional models, information is organized on the basis of form-oriented goals. In other words, perceptual or surface similarity provides the framework for classification. A given object may be categorized as an apple on the basis of its color and shape—perceptual attributes.

This idea of using perceptual similarity to carry out categorization processes is not without merit, and so it is not surprising that it also comprises a part of the assumptions underlying the theoretical models. However, surface similarity alone is not sufficient to explain categorization processes; therefore, the theory-based models expand upon this idea to include functional relationships, as explained previously. For this reason, theory-based models are considered to be function-oriented. This means that the underlying functions or relations of the features considered during categorization are the major factors driving the process, and perceptual similarity is a secondary product of this process.

Furthermore, because traditional models are form-oriented, they tend to have stable representations of concepts. Thus, the representation for a particular concept, whether it is a set of critical features (classical), a prototype, or a specific exemplar, does not change over time or across situations (i.e., they are context independent). For example, suppose an individual is confronted with the same object (e.g., rotten apple) that was classified as an apple at an earlier time. Assume that the previous classification was made solely on the basis of perceptual characteristics, such as color, shape, and edibility. If these same features were employed to make the subsequent classification, one might conclude that the now brown, inedible, and basically round object is a ball and not an apple. This might occur if one's representation for ball is round, red, and inedible, and one's representation for apple is round, red, and edible. Since the object matches on two features with ball (round and inedible) and only one feature with apple (round), one would then conclude, based on perceptual similarity, that the object is a ball. However, this categorization would be wrong since the object is actually a rotten apple. Theoretical models, however, could overcome this obstacle, since they incorporate contextual effects. When the brown, round, inedible object is perceived, the representation of apple might include the context-dependent subset of characteristics of a rotten apple and would provide a perfect match. In addition, at the moment of perception, a new representation could be constructed in working memory to incorporate information the individual has with regard to relationships. The individual may know that apples turn brown when they are rotten due to decay and that decayed or rotten apples are not good to eat and are, in effect, inedible. Knowledge of these functional relationships would further enable the individual to make an accurate classification.

Because of the diverse number of categorization models that exist, rather than asking the question "which model is correct?," the goal of predicting consumer behavior might be better served by the question "under what conditions do people engage in each type of categorization strategy?" For example, in any given situation a person could exercise one categorization model (classical, prototype, exemplar, or theory based) or a mixture of them (Busemeyer et al., 1984; Estes, 1986; Malt, 1989). There are two ways models might be mixed. Depending on the context or situation, one model might be chosen because it is more appropriate, even though the individual's cognitive flexibility allows for the application of other models. Second, the most efficient model for making a judgment may be employed first to perform a "first cut," and then if it is necessary, a second model could be employed that would yield more accurate information (Cohen and Basu, 1987).

In order to address the question of "which model is correct?," the process of categorization must be examined along two dimensions: the type of category representation and manner of information processing. In other words, for a given product in a particular context, do individuals employ feature-level representations or entity-level representations (such as brands) to construct categories? Furthermore, do they process available information about objects in an analytical or holistic fashion? Since a vast array of combinations of products and contexts are plausible, it stands to reason that categorization models must possess the flexibility to adapt to and function in the various complex and specific situations faced by consumers in their everyday product encounters (Cohen and Basu, 1987). The categorization mechanism(s) used (traditional versus theory based) in a particular situation may depend on a myriad of contingencies, including the context in which the categorization process takes place and characteristics of the individual, both enduring (e.g., prior knowledge) and situation-specific (e.g., mood) (see Basu, 1993; Cohen and Basu, 1987).

It might be argued that traditional similarity-based models could be "mixed," in the sense that in a given situation with a given product, an exemplar-based representation could be used to structure product knowledge, and in another situation with another product, the representation could take on the form of a prototype. This idea could be extended further with the notion that the same individual could represent a given situation with a given product via an exemplar representation at one point in time, and then represent the same event with a prototype representation at a later date. However, if this was the case, the individual would be inundated and probably overloaded with information—since each type of representation must be stored as a separate and stable concept, as provided for under the similarity-based models. A more cognitively efficient way to store information would be with a schema or frame-type representation as presented in the theory-based models. Under this class of models, representations are constructed "on the fly" in working memory; thus, essential information (context independent) can be activated along with knowledge that is contextually relevant (context dependent). Contextually irrelevant information is not activated, and cognitive efficiency is improved while maintaining cognitive stability and allowing for concept flexibility (Cohen and Basu, 1987). It can be seen that while the two types of models, similarity-based and theory-based, share some of the same characteristics, theory-based models allow for contingency effects. Thus, the particular model, or combination of models, that best represents the categorization process leading to evaluations may change across time and situations.

Table 4.1

**Comparison of Approaches to Categorization Theory**

| Aspect of categorization theory | Similarity-based approach | Theory-based approach | Mixed models approach |
|---|---|---|---|
| Concept representation | Similarity structure, attribute lists, correlated attributes | Correlated attributes plus underlying principles that determine which correlations are noticed | Each aspect of conceptual theory is explained by the comments in either the similarity or theory-based approach columns. The set of comments that applies for a given situation depends on the situation itself. Low-involvement tasks or in situations where a constraint exists (e.g., time, fatigue, etc.) lend themselves to the similarity-based approach, as this is less cognitively taxing. The reverse set of circumstances is more likely to induce a theory-based approach. However, in some cases more than one model may be employed to improve the efficiency of the categorization process |
| Category definition | Various similarity metrics, summation of attributes | An explanatory principle common to category members | |
| Units of analysis | Attributes | Attributes plus explicitly represented relations of attributes and concepts | |
| Categorization basis | Attribute matching | Matching plus inferential processes supplied by underlying principles | |
| Attribute weighting | Cue validity, Salience | Determined in part by importance in the underlying principles | |
| Interconceptual structure | Hierarchy based on shared attributes | Network formed by causal and exploratory links, as well as sharing of relevant properties | |
| Conceptual development | Feature accretion | Changing organization and explanations of concepts as a result of experience | |

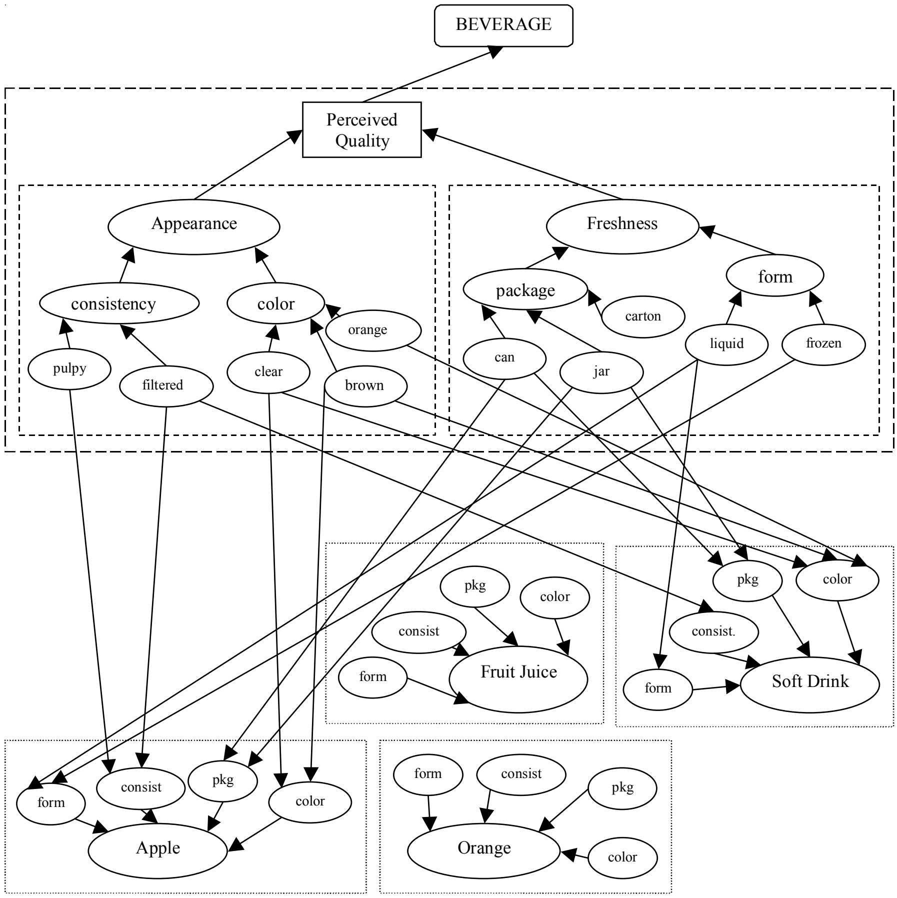
*Source:* Adapted from Douglas L. Medin. (1989) "Concepts and Contextual Structure." *American Psychologist,* 44, 1475.

### *Conclusions on Categorization*

The purpose of this section was to provide a general overview of categorization models and to integrate the two main classes of models (similarity-based and theory-based) within a unitary framework (see Table 4.1 for a comparison of similarity-based and theory-based approaches). A secondary goal was to communicate and emphasize the extreme influence and importance of context effects on categorization processes—especially with regard to one of the most critical issues in consumer behavior, evaluation formation.

In conclusion, several conjectures about categorization as it relates to consumer behavior can be made. For products, the possibility exists that "the consumer environment favors category definition in terms of specific exemplars rather than category-defining features . . . and this has considerable implications for evoked set formation and change" (Cohen and Basu, 1987, p. 470). Also, unlike the categories used in experimental research to compare categorization models, many consumer categories are goal related, which lend themselves to the application of theory-based

Figure 4.2 **Schematic of Nested Frames**




models, over similarity-based models. The advantage is that theory-based models incorporate the notion of similarity, as found in similarity-based models, along with the flexibility to respond to context effects.

## Development of the Evaluation Formation Model

### *Assumptions of the Model*

The model proposed in this chapter is a recursive frame model, which means that it can be visualized as nested within itself innumerable times at all levels of representation. At its broadest or most abstract level, the model can be considered one of concept evaluation. At this level, the overall product/brand evaluation serves as the categorization output and the attributes employed in the categorization process are those at the superordinate level, such as quality (Figure 4.2).

At the next level, the construct level, the model is operationalized in terms of a particular construct or superordinate-level attribute (i.e., quality), with a categorization output that is an evaluation or value of the superordinate attribute—such as acceptable, neutral, or unacceptable.

Of course, an underlying assumption of the model at this level is that the construct under consideration be salient to the product class and allow for the distinction of stimuli on this construct.

Basic-level attributes are the attributes that are preferred for use in the categorization process. However, these attributes often cannot be observed directly or within a reasonable period of time; therefore, their degree of existence must be determined via subordinate attributes. For example, workmanship and reliability might be two basic attributes for the quality construct with regard to cars. Unfortunately, values for these attributes are not easily discerned, and subordinate attributes such as price or make of the car and their related values might be used as surrogates. Of course, the level of the model and the attributes selected for use in the model depend on the product category of the stimuli. In addition, the different levels of operationalization of the model should be thought of as interconnected, such that the output of one influences the input of another and vice versa in a manner similar to a feedback loop.

Furthermore, more than one process may occur at the same time within the same level. For instance, the evaluation of a quality construct may be processed in parallel with the evaluation of a performance construct, and both outputs could serve as inputs to the broader process of forming a conceptual (i.e., product/brand) evaluation. Finally, the model is flexible in that attributes may become concepts at lower levels and values at higher levels, as well as the fact that the attributes that are considered to define a concept or higher-order attribute may change with context, level of evaluation, and product category (Barsalou, 1992).

Finally, implicit in the model is the understanding that categorization at a more fundamental level has already taken place (i.e., the identification of an object as a car) and a choice process has already occurred (i.e., the choice to evaluate luxury cars, as opposed to subcompacts, or to evaluate or consider quality as a salient attribute as opposed to performance). In other words, evaluation formation may be considered a dynamic process, such that there are multiple categorization tasks that must occur in order to lead to a final judgment or assignment to a set (Turley and LeBlanc, 1995). Importantly, the only stimuli that may be considered in the evaluation process are those that comprise the awareness set (i.e., those brands the consumer is aware of), which consists of the evoked, inert, and inept sets (Narayana and Markin, 1975).

### *Description of the Model*

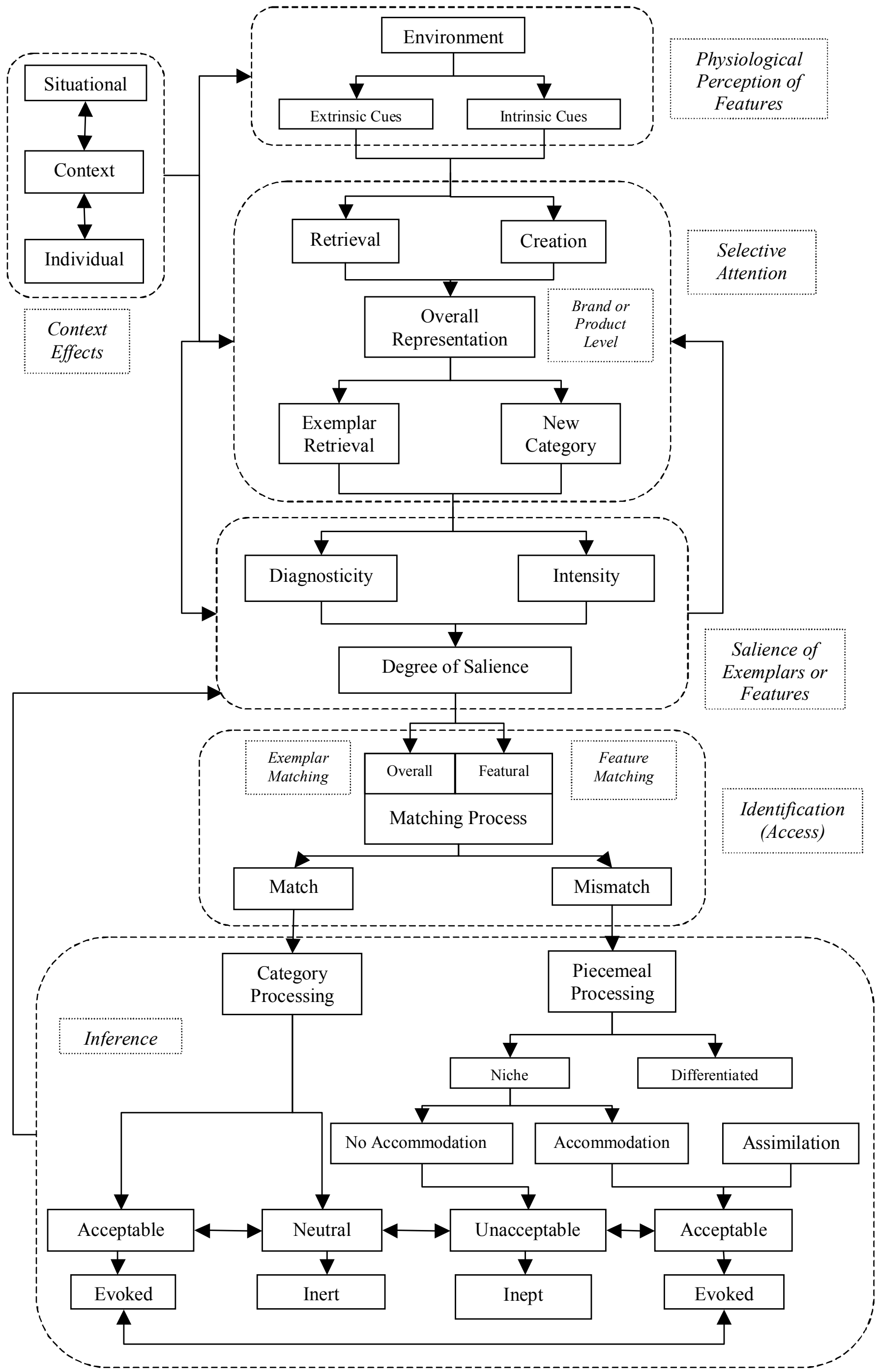
A categorization-based model of the product evaluation formation process is proposed (see Figure 4.3), and its components, as well as the theoretical considerations behind them, are broken down. The discussion begins with the context module and continues in order of appearance until the inference module is reached.

#### *Context Effects*

Context exerts a continuous influence on the physiological perception of features, selective attention, and salience of exemplars or features. Contextual factors consist of a wide array of variables, including situational factors such as the amount of time available for the categorization process and the type of task, as well as individual factors such as one's goals, theories, expertise, familiarity, and experience with the product category. One class of internal contextual factors involves the motivation to process information, which is related to the level of involvement that one has with the product or brand (Hutchinson and Alba, 1991). As an example of external constraints, Lamberts (1995) considered the influence of time pressure on the categorization of complex stimuli.

Tversky (1977) also makes the pertinent observation that perceived similarity, the major factor driving categorization processes, depends on context. In other words, the way in which the

Figure 4.3 **A Detailed Model of the Evaluation Formation (EF) Process**



objects are compared, or the characteristics on which they are compared is determined by one's frame of reference. Often, the frame of reference is not explicit and must be inferred from the general context. Usually, with natural or well-established categories, the majority of people tend to infer the same or similar frames of reference. However, with artificial (i.e., brands) or novel (i.e., new product class) categories, vastly different frames of reference may be inferred across subjects, depending on a multitude of contextual factors.

### *Physiological Perception*

Physiological perception is separated into perception of the environment, extrinsic cues, and intrinsic cues. The cues (extrinsic and intrinsic) may be produced by the environment, which influences "the way consumers encode product information" (Coupey and Nakamoto, 1988, p. 77). Extrinsic cues include price, brand name, packaging, and color. Intrinsic cues—for example, taste, texture, and the aroma associated with a product—are unique to each individual (Olson and Jacoby, 1972). Research shows that consumers tend to use both intrinsic and extrinsic cues when evaluating product quality (e.g., Jacoby, Olson, and Haddock, 1971; Richardson, Dick, and Jain, 1994; Simonson, 1989; Szybillo and Jacoby, 1974). The environment and its associated cues feed into the selective attention mechanism, which involves the operations of retrieval and creation.

### *Selective Attention*

Selective attention is a major component in the categorization-based model proposed here because "understanding the determinants of selective attention and elaboration in consumer information processing is important since the outcomes are crucial to product evaluation and memory for information which, in turn, impact brand preferences and choice behavior" (Malhotra and McCort, 2000/2001; Ratneshwar et al., 1990, p. 547).

*Retrieval Process.* Once the selective attention process has been engaged, one of two things must occur: retrieval or creation. Retrieval refers to the process where the stimulus information is matched against information in memory to determine whether an existing representation of the brand or product is present.[1] Schwarz and Bless (1992, p. 218) argue that "individuals who are asked to form a judgment about some target stimulus first need to retrieve some cognitive representation of it. In addition, they need to determine some standard of comparison to evaluate the stimulus." Research shows that context has an effect on retrieval since it affects accessibility, and accessibility is a product of two components. The first component is the amount of competing information contained in the same knowledge domain, and the second is the self-generated and environmentally available retrieval cues present at the time. Thus, different contexts lead to the retrieval of different information.

In addition, studies conducted on the structure of knowledge indicate that information is most frequently stored and organized as a brand unit (Johnson and Russo, 1984; Lynch and Srull, 1982). It follows then, owing to context effects on accessibility, that only a subset of information will be retrieved about a brand or product. Furthermore, this information will likely reflect only the information that was deemed to be most important, in terms of the individual's goals, at the time of initial encoding. In other words, with regard to the representation of an object or stimulus, the information may be stored in terms of the object's physical features, its function, its relation(s) to other objects, and properties inferred about the object. Therefore, depending on the task and object at hand, individuals retrieve and assimilate a select group of salient features or data from their knowledge store for the object in order to perform the necessary categorization task. This fact holds a great deal of significance for the second part of the categorization process, inference, since individuals tend to infer missing information from the information that is accessible (Lynch and Srull, 1982). For instance, if a consumer gives an automobile an acceptable quality rating, based on the surrogate attribute of price, the individual might also infer that comfort, another attribute associated with quality, will be a feature of the automobile.

*Level of Representation.* As it has been pointed out, context or frame of reference has a significant effect on product evaluations. This comes into play particularly during selective attention, where the level of representation (i.e., product or brand) is selected. It is postulated that all products have at least two category representations: the product schema and the brand schema. These schemas include expectations associated with the particular product or brand, including the usual attribute values, importance weights of attributes, the variability across brands or products on attributes, and so on (Sujan and Bettman, 1989). These two representations can be accessed independently or in conjunction with one another.

In most cases, however, consumers will retrieve a brand representation, since this is the representation most suited to evaluating comparable alternatives—the type of alternatives consumers usually face. The brand level is suited to comparable options (i.e., options from the same or similar product categories), since the brand provides a convenient way for consumers to chunk information. Furthermore, "comparability naturally describes alternatives whose attributes are represented dimensionally" (Johnson, 1984, p. 741). Therefore, within-attribute comparison (brand-level) strategies tend to be preferred to across-attribute comparisons (product level), since it is easier for consumers to compare alternatives directly on attributes and across brands.

Noncomparable alternatives (i.e., alternatives from different product categories) naturally tend to be evaluated at the product level, since this allows for the inclusion of more abstract attributes for comparison. Consumers may evaluate noncomparable alternatives in the same two ways as comparable alternatives: across attributes (product level) or within attributes (brand level). Evaluations of noncomparables across attributes occur at the product level, since "consumers simply combine attribute values into overall evaluations on which a direct comparison is made" (Johnson, 1984, p. 742). This is a more holistic evaluation process.

However, if a within-attribute strategy is pursued for noncomparable alternatives, then the attributes used for comparison must be considerably more abstract than those attributes used for comparison at the brand (comparable) level. For example, evaluating the level of benefit achieved by taking a train, plane, or car (product level/noncomparable alternatives) to a destination may involve consideration of attributes such as speed of transportation, cost, scenic value, or level of relaxation. On the other hand, determining the level of quality offered by various makes of cars (brand level/comparable alternatives) may require comparisons between the cars on the attributes of gas mileage, color, performance, or number of doors.

This leads one to the conclusion that within-attribute evaluations occur on a concrete-abstract continuum (Johnson, 1984, 1988; Johnson and Fornell, 1987; Malhotra, 2001; Malhotra and McCort, 2001). Thus, if the alternatives are comparable, the consumer will focus on the concrete attributes. However, as the alternatives become increasingly noncomparable, the consumer is forced to recognize increasingly abstract attributes in order to make comparisons within attributes for the initially noncomparable alternatives (Johnson, 1984, 1988). This continuum interfaces with the categorization perspective, since the concrete–abstract continuum can be equated with the subordination–superordination hierarchy of levels within categorization. Moreover, processing of concrete attributes can be viewed as a type of feature-based prototype categorization (because concrete attributes are usually evaluated in a dichotomous manner—the object either has or does not have the feature), and the processing of abstract attributes as a dimensional-based prototype categorization, where the dimensions encompass a continuum of possible values for the attribute (Johnson and Fornell, 1987). Processing at the entity level (i.e., across attributes) may be thought of as holistic-based prototype categorization.

*Creation Process.* Creation occurs if no relevant information is located in memory (i.e., retrieval is not possible), thus a representation must be created spontaneously. Regardless of whether retrieval or creation occurs, an overall representation is activated, and this representation can take on multiple forms for the same object, depending on the task at hand (i.e., the object may be represented at the brand or product level; see Cohen and Basu, 1987).

*Relationship to Salience.* Selective attention has a direct relationship to salience; more specifically, several factors have been identified as directing more attention to certain attributes of a stimulus. The first factor involves salience effects. These effects represent the phenomenon where physically salient events in the environment (i.e., eye-catching events; focus of a visual scene) capture a relatively large portion of attention. Similarly, novel or inconsistent information often commands the focus of attention. In addition, if information that is extreme in nature (i.e., highly positive or highly negative) is presented, it is usually paid more attention and assigned greater importance. It is postulated "that extremity and negativity both determine the 'informativeness' of a given piece of information, and that informativeness in turn determines both the attention paid to the information and the weight given to it in overall judgments" (Lynch and Srull, 1982, p. 32). Hutchinson and Alba (1991) demonstrate that perceptual salience directs consumers' attention to certain attributes; however, the extent to which these attributes enhance analytical learning is dependent on the relevance, or diagnosticity, of the attribute. In addition to salience effects, two other factors seem to have an effect on selective attention processes and salience: accessibility and familiarity (Johnson and Russo, 1984; Ratneshwar, Mick, and Reitinger, 1990).

Because consumers must create meaning out of a barrage of stimuli, selective attention acts as a screening mechanism in choosing which information to process in more detail. Context also influences this mechanism, and as a result, the individual factor of accessibility often plays a crucial role in the attention paid to and importance assigned to attributes. When an individual must evaluate a product of a known product class, the person may have a chronically accessible attribute—an attribute that is tied to the representation of the product—which comes easily to mind. If this is the case, the consumer often will direct his attention to that chronically accessible attribute and "process it more deeply and/or elaboratively" (Ratneshwar, Mick, and Reitinger, 1990, p. 548). Also, not surprisingly, consumers tend to assign more importance to that attribute. This result has important ramifications for marketers, since consumers tend to attend to and process information relevant to the chronically accessible attribute more efficiently, make more positive judgments with regard to a product containing the chronic attribute, and judge the chronic attribute to be more important than those that do not exhibit chronic accessibility. Thus, it is postulated that a relationship between selective attention and salience exists, since important attributes are often chronically accessible (Ratneshwar, Mick, and Reitinger, 1990).

Familiarity also plays an important but somewhat different role in selective attention and salience. First, consumers who are more familiar with an evaluation object will have better knowledge of alternatives to the evaluation object. Second, consumers with greater familiarity frequently have knowledge about what relationships to expect between features of products within a product class (e.g., the relationships between engine size, gas mileage, and acceleration in automobiles).

Finally, consumers with greater evaluation object familiarity possess the ability to select the relevant or salient information to attend to and disregard irrelevant information.

*Salience*

Once an overall representation is activated and related exemplars are retrieved or created in the selective attention process, salience of these exemplars and their features may be determined. Tversky (1977) proposed that the degree of salience is determined by two types of factors: diagnosticity and intensity. Intensity deals with factors that increase the signal-to-noise ratio (i.e., the brightness of light or the loudness of a tone). Diagnosticity, on the other hand, refers to "the classificatory significance of features, that is, the importance or prevalence of the classifications that are based on these features. Unlike the intensive factors, the diagnostic factors are highly sensitive to the particular object set under study" (Tversky, 1977, p. 342).

As stated previously, in order to simplify complex tasks, people often sort or group objects into clusters to reduce the amount of information they must handle and information processing demands. This has ramifications for the feedback loop between the diagnosticity aspect of salience and categorization output. Because people assign objects to clusters so that the similarity of objects within clusters is maximized relative to the similarity of objects between clusters (Rosch, 1975), the addition or deletion of objects can result in the reclustering of objects. A change in the objects comprising a cluster (or an evaluation set in the proposed model) may then alter the diagnosticity of particular attributes, depending on what attributes or dimensions were used to form the new clusters. This change in diagnosticity may then manifest itself in the alteration of perceived similarity between objects (Tversky, 1977). Furthermore, similarity may also be affected by changes in diagnosticity owing to context effects (i.e., selectively attending to a particular feature due to the nature of the task at hand or the surrounding environment). Thus, it is not similarity that defines the categories, but rather the categories that determine which objects are similar and along what lines they are similar (Medin, 1989).

After salience has been determined, the product evaluation categorization process begins. Product evaluations are evaluations assigned to individual products or brands, but are developed as a result of relative comparisons across brands or products. Therefore, the product evaluation process can be thought of in terms of a two-part categorization process: (1) access, or the process of deciding what something is, and (2) inference, or the process of making evaluations and/or assigning implicit attributes to an object (Barsalou, 1990). Although these two processes remain *conceptually* distinct, they are known to be interactive and cognitively dependent upon one another.

*Access*

Access is traditionally explained via three theories in the psychological literature on categorization: classical theory, prototype theory, and exemplar theory, each of which was explained earlier in this chapter. These theories are limited in that they do not account for the assumption that category structure and access are influenced by context (Barr and Caplan, 1987). To overcome this problem, goal-derived categories, context effects, and mixed models have been proposed, which suggest that people use both deep and surface similarity to form categories and assign category membership. Barr and Caplan (1987, pp. 398–399) take a related mixed models approach when they suggest that "Whether or not the object is judged to be a member of the category is going to depend not on characteristics of the object itself, but instead on the relationship it holds with the other entity or entities. In some situations the object may hold the appropriate relationship, and in other situations it may not hold this relationship." They go on to distinguish between intrinsic and extrinsic features, and they postulate that categories represented primarily by extrinsic features give rise to graded structure, as accounted for in prototype or exemplar models, whereas categories dominated by intrinsic features tend to adopt the all or none representation of classical categorization theory.

### *Inference*

The second component of categorization is inference. Of the two processes of categorization, inference is of particular interest to marketers because it allows consumers to make predictive judgments and evaluations about product attributes that are not explicitly stated in product information sources. For example, if a car was evaluated as being high quality, then one might infer that it is also comfortable. Inference is also important because it affects not only a consumer's initial impression of a product, but also his or her subsequent product choice.

Referring to the detailed model in Figure 4.3, a match or a mismatch may occur in the access process—leading to category-based or piecemeal processing, respectively. The categorization literature also points to mixed models, and one type of these, the "first-cut" model, is particularly relevant to the evaluation of products since it consists of two stages. In the first stage, surface (salient similarity) is used to make a "holistic" (entity level) or nonanalytical cut across attributes, whereas the second stage involves a more analytical cut via comparison within attributes (featural-level for concrete attributes and dimensional-level for abstract attributes) at the deeper level of relational similarity. Sujan (1985) refers to the nonanalytical cut as category-based evaluation and the analytical cut as piecemeal evaluation.

*Category-Based Processing.* If a match occurs, in other words, an object (i.e., product or brand) is classified as an example of a known category, any affect associated with the category or the object can be transferred to the object (Coupey and Nakamoto, 1988; Halstead, Page, and Dröge, 1991; Ruth, 2001). This process is illustrated in research concerning brand extension evaluations, which shows that the transfer of a core brand's evaluation (affect associated with a category) to a new extension becomes greater as the core brand and extension are perceived more similarly, or a "match" occurs (e.g., Aaker and Keller, 1990; Boush and Loken, 1991; Boush et al., 1987). Since emotions are also represented in memory as a type of categorical knowledge (Conway and Bekerian, 1987; Shaver et al., 1987), then evaluations of the object will be influenced by the emotional categories associated with it. Gregan-Paxton and John (1997) developed the consumer learning by analogy (CLA) model, which suggests that internal knowledge transfer occurs by either a schema-based or a similarity-to-exemplar process. This surface-level or low-involvement processing is what Sujan (1985) refers to as "category" processing. The transferred affect, depending on the stimulus, could be either acceptable, neutral, or unacceptable, and the object will fall into the evoked, inert, or inept set, respectively, depending on its acceptability level relative to the level associated with other objects under evaluation (i.e., a neutral-level assignment leads to the inert set and an acceptable-level assignment leads to the evoked set).

Concurrently, Sujan (1985) goes on to support the view that category-based evaluation is always attempted first, since it requires less cognitive effort and a lower level of involvement (see also Halstead, Page, and Dröge, 1991). If it is successful (i.e., a match occurs), then the affect associated with the evoked category is assigned to the stimulus (i.e., brand or product), and categorization occurs at the entity level. However, if a mismatch occurs, then piecemeal processing (i.e., high-involvement, analytical processing) must take place (Sujan, 1985), which is featural in nature for concrete attributes and dimensional in nature for abstract attributes (Johnson and Fornell, 1987). In addition, Sujan (1985) provides evidence that evaluations produced via category-based processing tend to be more extreme than those produced by piecemeal processing. It also is noted that experts tend to engage in category-based processing for matches and piecemeal processing for mismatches, whereas novices tend toward category-based processing regardless of or whether a match or a mismatch occurs. This implies that the evaluations of novices, on the whole, tend to be more extreme than those of experts, mainly because they are assumed to rely on a similarity-to-exemplar-based process (see Gregan-Paxton and John, 1997).

*Piecemeal Processing.* If a match is not made, then the individual must resort to deeper, more involved, and analytical processing called "piecemeal" processing (Sujan, 1985). This means that products are evaluated attribute by attribute. For example, when consumers are presented with atypical (versus typical) advertisements, they tend to resort to an analytical ad evaluation process (e.g., Goodstein, 1993). Under piecemeal processing, evaluations for each attribute are combined according to some rule or heuristic to arrive at an overall evaluation for the product. Furthermore, as compared to category-based processing, overall evaluations are reached more slowly and are less extreme in piecemeal.

## Research Design and Methodology

The empirical work presented here focuses on testing the model developed in the previous section. As was explained above (also seen in Figure 4.3), once the inference module is reached, the Evaluation Formation Process (EF) model requires processing to occur in one of two ways: category-based processing or piecemeal processing (Agarwal and Malhotra, 2005; Malhotra, 2005). This led to the conclusion that both parts of the model should be tested, hence the necessity for two parts in the research design. Part I tested the left-hand side of the model, category-based processing, which is more of a macro or holistic approach. Part II tested the right-hand side of the model, piecemeal processing, which is more of a micro level examination of the evaluation formation process since it occurs at the attribute level. The primary goal of both parts, however, was to determine the ability to predict set membership (evoked, inert, or inept) accurately. The methodology employed in Part I makes use of asymmetric multidimensional scaling (MDS). Part II is distinguished by the fact that four models (i.e., categorization based, self-explicated utility, conjoint, and hybrid conjoint) were tested and compared to one another to determine their relative prediction power. Also noteworthy is the fact that one of the models, the categorization-based model, was developed from the literature by the authors, specifically to test the piecemeal processing part of the EF model. Next, more detailed discussions of the category-based and piecemeal processing parts of the model are given, followed by discussions on sampling, the product category pretest, and questionnaire design and administration issues.

### *Part I: Category-Based Processing*

#### *Purpose*

This part of the research attempted to force category-based processing for a set of stimuli, comprised of *existing* brands, and then predict, through MDS, the group membership for each stimulus in the set at both the individual and cluster (subsegment) levels. The use of existing/known brand names as stimuli, without any description or list of attributes, forced the respondent to retrieve a previously stored representation and evaluation for each brand (category-based processing) in order to categorize it into one of the three sets (i.e., evoked, inert, or inept).

*Statistical Methods*

Both multidimensional scaling (MDS) and cluster analysis were used to test the category-based processing side of the model (Malhotra and Charles, 2002; Malhotra, Charles, and Uslay, 2004). These techniques allowed the set prediction ability of MDS to be explored at both the individual (disaggregate) and cluster (subsegment) levels. It was necessary to collect typicality or ideal point data on each stimulus from each respondent in order to locate the evoked set on the perceptual maps of respondents. Since this typicality/ideal point data is collected in addition to the perceptual data, the analysis is an external one. Although the external analysis creates more of a demand for data from the respondents, it is more stable than an internal analysis, since it does not confound typicality/ideal differences with differences in perceptions (Hair et al., 1998; Malhotra, 2004).

***Part II: Piecemeal Processing***

*Purpose*

This part of the research sought to force piecemeal processing to occur for a set of *hypothetical* stimulus profiles, and then predict, through traditional conjoint analysis, the self-explicated utility model, a categorization-based methodology, and a main-effects hybrid conjoint model, the group membership (evoked, inert, or inept) for each profile or stimulus in the set at the individual level. The use of hypothetical profiles forced the respondent to engage in piecemeal processing because the respondents did not have any previously stored representations or evaluations for the stimuli and out of necessity used the attributes and their corresponding values given in the profiles to determine set membership. The final step in this part of the empirical investigation was to compare the four methodologies in order to determine which method was a better tool for prediction.

*Statistical Methods*

In this part of the research, four methodologies were employed: traditional conjoint analysis, self-explicated utility, a categorization-based methodology, and main-effects hybrid conjoint analysis. Although discussions of the traditional conjoint, self-explicated, and hybrid conjoint models may be found in the literature (e.g., Akaah and Korgaonkar, 1983; Malhotra, 2004), the categorization model, developed by the authors, is briefly discussed.

*Categorization-Based Model.* As discussed earlier, this model views salience as being comprised of two components: diagnosticity and intensity (Tversky, 1977). In the literature, two other well-known conceptualizations of salience exist. The first is by Alpert and colleagues (Alpert, 1971, 1979; Myers and Alpert, 1968), who adopted a concept similar to Tversky's salience and called it *determinance.* Determinance implies that a particular attribute is both important (i.e., in terms of product evaluation) and sufficiently different (i.e., variability exists among brands along the levels or values they possess for an attribute); thus, it is the product of importance and difference.[2] A second approach is found in the perceived quality literature where Olson and Jacoby

(1972) proposed that the probability of an attribute's use is based on the product of its predictive value (PV) and confidence value (CV). PV is the extent to which the consumer perceives or believes that the cue is useful for categorization, and CV is "defined as the degree to which a consumer is confident in his ability to accurately perceive and judge that cue [or attribute]" (Olson and Jacoby, 1972, p. 175).

In an attempt to tie together these various ideas regarding salience, the authors relate Alpert's and Olson's frameworks to Tversky's two components: diagnosticity and intensity. Tversky, and Gati (1978, p. 90), proposed that "a feature may acquire diagnostic value (and hence become more salient) in a particular context if it serves as a basis for classification in that particular context." This concept of diagnosticity closely parallels the idea of the difference component in Alpert's work (Alpert, 1971; Myers and Alpert, 1968) and predictive value in Olson and Jacoby's (1972) work. Intensity is paralleled by CV, which is virtually synonymous with the concept of intensity in the attitude literature, and the importance component alluded to in Alpert's work is captured by the concept of salience (i.e., the product of diagnosticity and intensity, as shown in Figure 4.3). Therefore, it seems that in order to capture salience or importance one must measure diagnosticity/difference (DD) and CV/intensity (CV). Thus, salience/importance can be viewed as the product of these two components.

Salience does not present the complete picture, however, for the absolute level of acceptability must be taken into account (Myers and Alpert, 1968). This means that the values the attributes take on may be acceptable or unacceptable, and as such "it is always possible that some feature . . . might be totally unacceptable to respondents, so that [this] product characteristic would be rated very low" (Myers and Alpert, 1968, p. 18). Therefore, this facet must also be included in any attempt to describe product evaluation. If one assumes that acceptability is a matter of degree (i.e., its values lie along an acceptability continuum), and that the more typical the level the more acceptable it is, one can operationalize this measure from a categorization perspective via level of typicality for attribute levels. The inclusion of the level of typicality/acceptability may be introduced into the analysis simply by multiplying it by the degree of salience (i.e., salience = $DD \times CV$).

For the formulation of the categorization-based model, a process similar to the self-explicated utility model, as described in Green, Goldberg, and Montemayor (1981) was employed. The categorization-based methodology calculates the total categorization score $(C_h)$ of an alternative $(h)$ by summing the products of the self-explicated measures of diagnosticity/difference $(DD_j)$ and confidence value/intensity $(CV_j)$ for each attribute $(j)$, as well as acceptability/typicality level scores $(a_{ij}^{(h)})$ for each level $(i)$ of each attribute $(j)$:

*Categorization-Based Model:* $$C_h = \sum_{j=1}^{J} DD_j CV_j a_{ij}^{(h)}$$

Thus, it can be seen that the categorization-based score $(C_h)$ is arrived at via a method that is somewhat parallel to the self-explicated utility model and, to some extent, conjoint analysis. In the categorization-based model, not only are the values for all levels of each of the attributes and the values for the salience/importance of each attribute (captures variance within the attribute) used to arrive at an overall score for each alternative, as is the case in the self-explicated model and conjoint analysis, but the measure of salience is arrived at by the use of two direct measures (DD and CV) instead of the single direct measure used in the self-explicated utility model and the indirect measure used in conjoint. Thus, more information is captured by the categorization-based method, as compared to the self-explicated utility model and conjoint method.

Table 4.2

**Pretest Results: Factors and Levels**

| Factors | Levels | | |
|---|---|---|---|
| Price of meal<br>(single burger, regular fries, medium drink) | $3 | $4 | $5 |
| Quality of ingredients<br>(quality of ingredients used in preparing the meal) | Low quality | Intermediate quality | High quality |
| Taste<br>(food is properly cooked, has good flavor) | Below average | Average | Above average |
| Friendliness of service<br>(staff are helpful, alert, polite, and responsive) | Unfriendly | Indifferent | Genuinely friendly |
| Speed of service<br>(service is timely, food is served hot, order is correct) | Unreasonably slow | Satisfactory, but could be quicker | Very quick |
| Cleanliness of restaurant<br>(dining or eating area is clean) | Somewhat unclean | Moderately clean | Very clean |
| Healthiness of food<br>(e.g., nutritional value, fat content) | Somewhat unhealthy | Moderately healthy | Healthy |

### *Product Category Pretest*

Based on a pretest of 31 student subjects, fast-food hamburger restaurants were selected as the stimulus category. The top 10 rated restaurants with regard to frequency (i.e., how many times they were listed by the subjects) were selected as the stimulus set for Part I, which utilized existing brands. Also, a master list of attributes used in choosing a fast-food hamburger restaurant was compiled from the attributes given by the student subjects.

To determine the factors for testing the piecemeal processing part of the model, Part II, seven main attributes were selected for further consideration on the basis of their frequency of occurrence. The number of levels for each factor was set at three, since membership was to be predicted for three sets (evoked, inept, and inert). Appropriate level names were decided upon and can be found in Table 4.2.

### *Survey Design*

The questionnaire utilized for this study consisted of an instruction sheet and four sections. In the first section, respondents were asked about their familiarity with and frequency of visits to the fast-food restaurant stimuli. In the second section, data was collected for the category-based processing part of the model. Respondents were asked to state whether they found each stimulus to be acceptable, neither acceptable nor unacceptable, or unacceptable for eating fast-food hamburgers by circling the appropriate letter A, N, or U. Dissimilarities data for the category-based processing MDS analysis were then solicited. However, before the data were obtained, respondents were presented with a scenario. They were asked to assume that they had been shopping in a mall and were going to the food court, where all the restaurants were present, to eat lunch. This assumption was necessary to negate any context effects that might arise as a result of location or the type of meal to be consumed. The respondents were then presented with a list of the 10 restaurants, where they considered each restaurant in turn (the anchor), assumed it was the most typical, and ranked the remaining restaurants in terms of their similarity to the anchor restaurant (1 = most similar, 9 = least similar). This resulted in asymmetric dissimilarities data (Green and Rao, 1972). It was important to capture the asymmetry of such data because this is congruent with the categorization framework, which espouses the idea that similarity is asymmetric, largely due to context effects such as "frame of reference" or goals (Barsalou, 1983, 1992; Tversky, 1977). The last part of the second section collected ratings and rankings of both how typical and how ideal each restaurant was of an acceptable restaurant. This information was obtained to carry out the external unfolding MDS and cluster analyses.

The third section requested data for testing the piecemeal processing models, namely, the conjoint, hybrid, self-explicated, and categorization models. This section required the use of 27 hypothetical cards or profiles. In order to develop the hypothetical profiles, the seven factors at three levels each, as shown in Table 4.2, were used. An appropriate $3^7$ orthogonal main-effect plan with 18 profiles was selected, and the hypothetical profiles (cards) were constructed. In addition, for the purpose of validating the four models, a holdout sample of 9 profiles was constructed. A total of 27 cards resulted.

For the purposes of evaluating the results of the four models, the respondents were asked to rate each card on a 1 to 10 Likert scale (1 = completely unacceptable, 10 = completely acceptable) with regard to how they felt about eating at the restaurant described on the card. This information was then used as the dependent variable in a disaggregate conjoint analysis and for the hybrid conjoint analysis. Next, the respondents were asked to sort the 27 profiles (profiles 1–18 comprised the estimation sample and profiles 19–27 the holdout or validation sample) into three piles, representing acceptable, neither acceptable nor unacceptable, and unacceptable profiles of restaurants for eating fast-food hamburgers. Then they were asked to circle the letter (A, N, U) next to each card that corresponded to that card's pile assignment.

In order to test the categorization-based model, measures of DD and CV were obtained. To measure DD, respondents indicated the degree of difference they perceived among the brands in the stimulus set on each attribute, using a 10-point Likert scale.[3] Likewise for CV, respondents indicated the level of confidence they felt regarding their ability to perceive differences in the attributes for the brands in the stimulus set. Also, the respondents were required to rate each level of each attribute (Green, Goldberg, and Montemayor, 1981; Myers and Alpert, 1968) on the basis of its typicality for an acceptable fast-food hamburger restaurant, on a scale from 1 to 10 as operationalized in Green, Goldberg, and Montemayor (1981).

In the last part of the third section, desirability ratings for each level of each attribute (collected the same way as typicality ratings for attribute levels) and importance ratings for each attribute (collected on a 10-point Likert scale identical to those for DD and CV) were solicited for the self-explicated utility model. This information, along with the information for conjoint analysis requested earlier in the survey, provided the necessary information for conducting hybrid conjoint analysis.

The final and fourth part of the questionnaire solicited general information, such as respondent's knowledge level, willingness, interest, and fatigue. Also, the respondent's sex and name were requested. A total of 262 completed questionnaires were obtained from undergraduate students.

## Statistical Analyses and Results

### *Part I: Category-Based Processing*

The analysis for this part of the model was conducted using MDS techniques at both the individual (disaggregate) and cluster (subsegment) levels.

#### *Individual-Level MDS*

The asymmetric dissimilarities data on the set of 10 fast-food restaurants, collected from each individual, was used as input in the nonmetric MDS. A two-dimensional solution was chosen because this made the spatial map easy to use and interpret. This initial MDS analysis resulted in a spatial/perceptual map of the 10 restaurants or stimuli for each respondent. The stimulus coordinates for each respondent's map were saved and used as input for the second MDS procedure—the external MDS that mapped typical/ideal points onto the perceptual maps.

Once the above analyses were completed, attention was then returned to the major emphasis of this chapter—predicting set membership. In order to accomplish this task, it was first necessary to calculate the distances between each stimulus point and the corresponding typicality/ideal point for each respondent. Then using these distances, the 10 restaurants were ranked from smallest to largest.[4] Assuming that the evoked sets would be comprised of the most typical/ideal acceptable restaurants, the $x$ highest ranked stimuli represented the individual's evoked set, the $y$ lowest ranked stimuli the inept set, and the remaining stimuli the inert set ($x$ = number of stimuli judged acceptable (A) by the respondent, $y$ = number of stimuli judged unacceptable (U) by the respondent—this data was directly solicited from the respondent).

Finally, the validity of these results was examined by comparing the empirical results (i.e., the particular restaurants predicted to be in each set) to the self-reported membership (i.e., the acceptability of the restaurants as judged by the respondents on the questionnaire) for both the typicality and idealness data. This examination was performed over all 262 respondents, since looking at the results for each individual was impractical. The results of this analysis, which yielded classification percentages or hit ratios for overall set membership, evoked set membership (A), inert set membership (N), and inept set membership (U) are shown in Table 4.3.

Considering the strong correlation between the typical and ideal measures, the overall results of the individual-level analysis were similar for both typicality (69.6%) and idealness (71.5%) anchored sets. Another pleasing result was the fact that both measures performed better than chance. These results lend support to the use of asymmetrical MDS as a tool for predicting set membership at the individual level.

#### *Cluster-Level MDS*

Stimulus coordinates for each individual's map were used to cluster the respondents on the basis of the similarity of their perceptual maps. Clustering all 262 respondents resulted in a five-cluster solution, with cluster sizes of 49, 24, 38, 62, and 89. Once the respondents were clustered on the basis of perceptual similarity, external unfolding MDS was performed for each cluster. The main theme of predicting set membership was returned to via an analysis to access the predictive ability of the subsegment or cluster level MDS. In order to do this, the stimuli that fell into the evoked, inept, and inert sets for each cluster were identified in the manner discussed previously in the individual analysis, using averages of respondents' self-reported set sizes and acceptability ratings for the stimuli, and aggregate maps for each cluster.

Table 4.3

**Summary of Correct Predictions (Hit Ratios) of Individual Level MDS**

Number of Correct Predicted Rankings
(n = 262 respondents x 10 = 2,620)[a]

| Set | Number of items in set | Most typical | Most ideal |
|---|---|---|---|
| Acceptable (Evoked) | 1,381 | 1,095 (79.3) | 1,107 (80.2) |
| Neutral (Inert) | 891 | 550 (61.7) | 561 (63.0) |
| Unacceptable (Inept) | 347 | 178 (51.3) | 204 (58.8) |
| Overall[a] (Total) | 2,619 | 1,823 (69.6) | 1,872 (71.5) |

*Note:* Values in parentheses represent the percentage of correct predictions.
[a]Due to one missing rating for set acceptability (A, N, U) for the restaurants, the total number of actual items is 2,619 instead of 2,620.

Again, as in the individual-level analysis, the validity of these results was examined by comparing the empirical results (i.e., the particular restaurants predicted to be in each set) to the averages of respondents' self-reported set sizes for both the typicality and idealness data, on a cluster-by-cluster basis. This examination was performed over all 262 respondents who comprised the five clusters. The results of this analysis yielded classification percentages or hit ratios for overall set membership, evoked set membership (A), inert set membership (N), and inept set membership (U) for each cluster (1–5) and all clusters combined (see Table 4.4).

The individual cluster results were satisfactory but are not presented because of space constraints. The combined cluster results were substantially above maximum chance for both the typical and ideal anchored sets. Thus, the results indicated that the MDS model was a good predictor of set membership at the cluster level. Furthermore, the similar results of the highly correlated measures of typicality and idealness provided further support for this methodology's capacity for set membership prediction.

***Part II: Piecemeal Processing***

Standard procedures described in the literature were used to test the piecemeal side of the EF model, via the categorization-based, self-explicated utility, conjoint, and hybrid conjoint models. The internal validity of the model, determined by calculating Pearson's product moment correlation for the predicted ratings versus the ratings given by the respondent for the holdout cards, was deemed satisfactory. In addition, predictive validity tests were carried out to access the models' abilities to predict set membership—the major focus of the investigation. The results of these analyses are presented in Table 4.5.

The hybrid model has an edge in predictive performance over the other three models. This edge was maintained for the percentage of acceptable or evoked set predictions but was lost to the traditional conjoint model for the percentage of inert set predictions and to the self-explicated utility model for inept set prediction. However, overall the traditional and hybrid conjoint models, along with the self-explicated utility model performed almost equally well—substantially

Table 4.4

**Summary of Correct Predictions (Hit Ratios) of Cluster Level MDS: All Clusters Combined (5 clusters total)**

Number of Correct Predicted Rankings
(n = 262 respondents)

| Set | Number of items in set | Most typical | Most ideal |
|---|---|---|---|
| Acceptable | 28 | 23 | 23 |
| (Evoked) | | (82.1) | (82.1) |
| Neutral | 17 | 11 | 12 |
| (Inert) | | (64.7) | (70.6) |
| Unacceptable | 5 | 2 | 3 |
| (Inept) | | (40.0) | (60.0) |
| Overall | 50 | 36 | 38 |
| (Total) | | (72.0) | (76.0) |

*Note:* Values in parentheses represent the percentage of correct predictions.

Table 4.5

**Summary of Correct Predictions (Hit Ratios) of Holdout Sample Evaluations**

Number of Correct Predicted Rankings
(n = 262[a] respondents x 9 = 2,358[b])

| Set | Number of items in set | Categorization based | Self-explicated utility | Traditional conjoint | Hybrid conjoint |
|---|---|---|---|---|---|
| Acceptable | 965[a] | 519 | 725 | 730 | 735 |
| (Evoked) | | (53.8) | (75.1) | (75.7) | (77.7) |
| Neutral | 777 | 370 | 465 | 486 | 473 |
| (Inert) | | (47.6) | (59.9) | (62.6) | (61.8) |
| Unacceptable | 612 | 280 | 429 | 425 | 424 |
| (Inept) | | (45.6) | (70.1) | (69.4) | (69.9) |
| Overall | 2,354[b] | 1,166 | 1,619 | 1,641 | 1,632 |
| (Total) | | (49.5) | (68.8) | (69.7) | (70.4) |

*Note:* Values in parentheses represent the percentage of correct predictions.

[a]As explained in the text, hybrid conjoint only utilized 258 respondents; thus the number of items for the hybrid model are as follows: A = 946, N = 765, U = 607, and overall = 2,318.

[b]Due to four missing ratings for set acceptability (A, N, U), the total number of actual items is 2,354 instead of 2,358.

outperforming the categorization-based model. It should also be noted that all four models, including the categorization model, performed better than chance.

A repeated measures design ANOVA was also carried out to determine if there was any significant difference between the mean hit ratios of overall set membership for the four models. The mean overall set membership hit ratios found in Table 4.5 proved to be significantly different at the $p = 0.000$ significance level. As indicated through simple observation, the categorization mean was lower than the means for the other models. This indicated that the categorization-based model did not provide as good a fit to the data; hence, this model should be reformulated for future research efforts. Perhaps, operationalizing salience as the square root of $DD$ x $CV$ will improve the prediction of this model.

## Conclusions and Contributions

The first goal of this chapter was to provide a comprehensive review of the categorization literature in both the psychology and marketing fields, with special emphasis on the categorization processes that underlie many consumer behaviors, in particular, evaluation formation. The authors discussed the main classifications of categorization models, similarity-based and theory-based, as well as the mixed models approach, which reflects a combination of the two traditional views and allows for contingency effects. With respect to each model type, the various levels within category structure were distinguished and the extent to which category members exhibit graded structure was discussed. This literature review provided the foundation for developing the evaluation formation model, which assists in predicting whether individuals will engage in category-based versus piecemeal processing in order to assign set membership to marketing stimuli.

The overriding goal of the empirical study was to investigate the proposed evaluation formation model in terms of set membership prediction. This was approached in two parts: category-based processing and piecemeal processing. First, category-based processing was tested, using asymmetrical MDS techniques to investigate set membership relative to existing or known products. Second, piecemeal-based processing was tested, using four different methodologies (categorization based, self-explicated utility, traditional conjoint, and hybrid conjoint) to compare their predictive abilities for set membership regarding new, unknown, or hypothetical products.

### *Managerial Implications*

The prediction of set membership as a result of the category-based and piecemeal processing methodologies, as well as the evaluation formation process presented in this chapter, hold significant implications for both academics and practitioners. As implied earlier, in order for marketers to get a consumer to choose the product offered by their firm, they must first get the product into the awareness set and then into the evoked set of the consumer. The second of these tasks is somewhat more difficult than the first and requires that marketers have an understanding of the evaluation process. By influencing various aspects of the evaluation process, such as the attributes utilized, the way the attributes are processed, and the level of processing, a marketer can move a product from the inert or inept set to the evoked set. The end result or final categorization of the product via the evaluation process may be changed by altering both extrinsic attributes, such as brand name and advertising emphasis, as well as by altering intrinsic attributes such as improving quality so that the brand is perceived to be new or improved (Narayana and Markin, 1975). Thus, discovering consumers' set memberships of products, as well as understanding the processes themselves, is imperative to selling products (i.e., positioning them in the evoked set of the consumer).

With the above discussion in mind, the reader must also remember that the overall evaluation of a product is relative. Therefore, those brands/products in the awareness set may move from the inert set to the evoked or inept set due to new information, product trial, or altered consumer needs or preferences. In addition, the strategy of considering evaluations in terms of set classification means that practitioners have yet another tool to shape market segmentation strategies. By learning the percentage of the market aware of a brand and then the percentage of aware consumers in the evoked, inert, and inept sets, a marketer could determine where his or her product stands in relation to competitors' products and the courses of action to take. For example, a plausible course of action for consumers that exhibit lack of awareness would be intensified advertising. For consumers in the evoked set, a marketer should continue to confirm the evaluations the consumers hold about the product, especially through advertising, whereas inert set consumers might be moved into the evoked set through comparative advertising or free samples. However, regardless of whether evoked, inert, inept set consumers were targeted, the appeals or strategies directed toward these consumers could be better formulated if the process behind the formation of these evaluations was understood (Narayana and Markin, 1975). Therefore, by identifying the process of evaluation formation, such as through the EF model proposed in this chapter, and the set membership of products of interest, this information may be used to design consumer appeals or redesign products either through manipulating intrinsic or extrinsic cues or a combination of both.

### *Contributions*

This chapter makes several contributions in terms of its topic, theoretical model development, and methodological applications. First, the driving empirical goal of this study, predicting set membership, was unique. Few studies have been performed with this objective in mind.

With regard to theoretical model development, two contributions distinguish this work. First, after an extensive review of the pertinent literature, a model of the evaluation formation process was developed. By explicating and providing a theoretical framework for the formation of evaluations, this model makes a significant contribution to the marketing field. Second, a categorization-based methodology, which represents both a theoretical and methodological contribution, was developed from the proposed EF model to predict set membership. Although this model did not perform as well as was expected, it still may possess significant potential once it has undergone reformulation and refinement. Continuing with methodological contributions, this work integrated asymmetrical MDS as a methodology. Although knowledge of categorization theory suggests that similarity is asymmetric, MDS analyses are rarely performed using asymmetrical data. Rather, the less complex type of data, symmetric data, is commonly used. Along these same lines, the MDS methodology employed in this study was also somewhat unique since it utilized external unfolding MDS. This technique is not as commonly used in marketing research as is internal unfolding MDS and is more difficult to execute, especially with a large number of subjects as was used in this empirical investigation. The final contribution of this chapter is that it adds to the existing body of work that compares the predictive validity of conjoint, hybrid conjoint, and self-explicated models (Akaah and Korgaonkar, 1983). Authors of this literature have repeatedly called for more work in this area.

### *Recommendations for Future Research*

Based on the results of this empirical investigation, several recommendations can be made. First, the set prediction abilities of the category-based asymmetrical MDS and piecemeal processing conjoint, hybrid conjoint, and self-explicated utility models were very encouraging. More work should be conducted on the predictive capabilities of these models, particularly with representative samples that are generalizable. Also, effort should be devoted to empirically determining set size, rather than relying on self-reported measures. In addition, the dynamic aspects of set composition are especially important to consider in consumer behavior research (see Turley and LeBlanc, 1995). For example, future research should examine the processes underlying the movement of brands or products from an individual's inert or inept set to his or her evoked set. In other words, how are consumers able to reconsider brands that have been previously rejected?

Second, on the basis of the results of this investigation, future research directions should include reformulating and refining the categorization-based model so that it can realize its full potential. For example, the identification of salient attributes and how they affect product evaluations has significant potential with regard to brand extensions, both within and between product classes. "These ideas on brand name transferability are closely related to theories of categorization which suggest that the greater the [similarity, through feature overlap or shared benefits], between items, the greater the likelihood that such items will be perceived to belong to the same cognitive category" (Chakravarti et al., 1990, p. 911).

Finally, more detailed theories need to be developed to explain the evaluation formation process so that set membership can be better understood and predicted. Concurrently, the methodologies put forth in this chapter need to be explored further with regard to their abilities to predict set membership, and other existing methodologies need to be refined or new methodologies developed to incorporate knowledge of the evaluation formation process, and hence set membership prediction, as it is discovered. It is hoped that this study serves to generate more insight into the evaluation formation and set prediction processes, as well as stimulate more interest in these important topics.

## Acknowledgment

The authors wish to thank Larry Barsalou for providing helpful comments on an earlier version of this chapter.

## Notes

1. While it is recognized that representation may occur at the brand or the product level, for the purposes of discussing this model, the terms *brand*, *product*, and *stimuli* will be used interchangeably to refer to the object being categorized.

2. For example, Myers and Alpert (1968, p. 14) explain that "in asking consumers to evaluate such automobile attributes as power, comfort, economy, appearance, and safety, consumers often rank safety as first in importance. However, these same consumers do not see various makes of cars as differing widely with respect to safety; therefore, safety is not a determinant attribute or feature."

3. Alpert (1971) and Olson and Jacoby (1982) use five-point scales, while Green, Goldberg, and Montemayor (1981) use a ten-point scale for rating the level of attributes. Since Green, Goldberg, and Montemayor's (1981) work is more related to the ideas underlying this paper's framework and allows more variability in the data, and because the four measures (acceptability level, DD, II, and CV) that determine the overall attribute rating should have equal weights, a ten-point scale was employed for all four measures.

4. With a negative-negative or positive-positive typical/ideal point, the closer a stimulus is to the point, the more similar it is. With a negative-positive or positive-negative typical/ideal point, the farther away the stimulus is from the point, the more similar it is. The direction of the typical/ideal points was accounted for in determining similarity in the empirical results.

## References

Aaker, David, and Kevin Lane Keller. (1990) "Consumer Evaluations of Brand Extensions." *Journal of Marketing*, 54 (1), 27–41.

Agarwal, James, and Naresh K. Malhotra. (2005) "Integration of Attitude and Affect: An Integrated Model of Preference, Intention, and Choice." *Journal of Business Research*, forthcoming.

Ahn, Woo-Kyoung, and Douglas L. Medin. (1992) "A Two-Stage Model of Category Construction." *Cognitive Science*, 16 (1), 81–121.

Akaah, Ishmael P., and Pradeep K. Korgaonkar. (1983) "An Empirical Comparison of the Predictive Validity of Self-Explicated, Huber-Hybrid, Traditional Conjoint, and Hybrid Conjoint Models." *Journal of Marketing Research*, 20 (May), 187–197.

Alba, Joseph W., and J. Wesley Hutchinson. (1987) "Dimensions of Consumer Expertise." *Journal of Consumer Research*, 13 (March), 411–454.

Alpert, Mark I. (1971) "Identification of Determinant Attributes: A Comparison of Methods." *Journal of Marketing Research*, 8 (May), 184–191.

———. (1979) "Unresolved Issues in Identification of Determinant Attributes." *Advances in Consumer Research*, 7, 83–88.

Ashby, F. Gregory, and Shawn W. Ell. (2002) "Single Versus Multiple Systems of Learning and Memory." In *Stevens' Handbook of Experimental Psychology: Vol. 4: Methodology in Experimental Psychology*, 3rd ed., ed. H. Pashler and J. Wixted, pp. 655–691. New York: John Wiley and Sons.

Ashby, F. Gregory, and Ralph E. Gott. (1988) "Decision Rules in the Perception and Categorization of Multidimensional Stimuli." *Journal of Experimental Psychology: Learning, Memory and Cognition*, 14 (1), 33–53.

Ashby, F. Gregory, and W. Todd Maddox. (1990) "Integrating Information from Separable Psychological Dimensions." *Journal of Experimental Psychology: Human Perception and Performance*, 16 (3), 598–612.

———.(1992) "Complex Decision Rules in Categorization: Contrasting Novice and Experienced Performance." *Journal of Experimental Psychology: Human Perception and Performance*, 18 (1), 50–71.

———. (1993) "Relations Between Prototype, Exemplar, and Decision Bound Models of Categorization." *Journal of Mathematical Psychology*, 37 (3), 372–400.

———. (1998) "Stimulus Categorization." In *Measurement, Judgment, and Decision Making*, ed. Michael H. Birnbaum, pp. 251–301. San Diego, CA: Academic Press.

Austin, John T., and Jeffrey B. Vancouver. (1996) "Goal Constructs in Psychology: Structure, Process, and Content." *Psychological Bulletin*, 120 (3), 338–375.

Barr, Robin A., and Leslie J. Caplan. (1987) "Category Representations and Their Implications for Category Structure." *Memory and Cognition*, 15 (5), 397–418.

Barsalou, Lawrence W. (1982) "Context-Independent and Context-Dependent Information in Concepts." *Memory and Cognition*, 10 (1), 82–93.

———. (1983) "Ad Hoc Categories." *Memory and Cognition*, 11 (3), 211–227.

———. (1985) "Ideals, Central Tendency, and Frequency of Instantiation as Determinants of Graded Structure in Categories." *Journal of Experimental Psychology: Learning, Memory and Cognition*, 11 (4), 629–654.

———. (1987) "The Instability of Graded Structure: Implications for the Nature of Concepts." In *Concepts and Conceptual Development: Ecological and Intellectual Factors in Categorization*, ed. U. Neisser, pp. 101–140. Cambridge: Cambridge University Press.

———. (1989) "Intraconcept Similarity and Its Implications for Interconcept Similarity." In *Similarity and Analogical Reasoning*, ed. S. Vosniadou and A. Ortony, pp. 76–121. Cambridge: Cambridge University Press.

———. (1990) "Access and Inference in Categorization." *Bulletin of the Psychonomic Society*, 28 (3), 268–271.

———. (1991) "Deriving Categories to Achieve Goals." In *The Psychology of Learning and Motivation: Advances in Research and Theory*, 27, ed. G.H. Bower, pp. 1–64. San Diego, CA: Academic Press.

———. (1992) "Frames, Concepts, and Conceptual Fields." In *Frames, Fields, and Contrasts: New Essays in Semantic and Lexical Organization*, ed. E. Kittay and A. Lehrer, pp. 21–74. Hillsdale, NJ: Erlbaum.

Basu, Kunal. (1993) "Consumers' Categorization Processes: An Examination with Two Alternative Methodological Paradigms." *Journal of Consumer Psychology*, 2 (2), 97–121.

Boush, David M. (1993) "Brands as Categories." In *Brand Equity and Advertising: Advertising's Role in Building Strong Brands*, ed. David A. Aaker and Alexander Biel, pp. 299–312. Hillsdale, NJ: Erlbaum.

Boush, David M., and Barbara Loken. (1991) "A Process-Tracing Study of Brand Extension Evaluations." *Journal of Marketing Research*, 28 (1), 16–28.

Boush, David M., Shannon Shipp, Barbara Loken, Ezra Genturck, Susan Crockett, Ellen Kennedy, Betty Minshall, Dennis Misurell, Linda Rochford, and Jon Strobel. (1987) "Affect Generalization to Similar and Dissimilar Brand Extensions." *Psychology and Marketing*, 4 (3), 225–237.

Brewer, William F., and Glenn V. Nakamura. (1984) "The Nature and Functions of Schema." In *Handbook of Social Cognition*, 1, ed. R. Wyer, Jr., and T. Srull, pp. 119–160. Hillsdale, NJ: Erlbaum.

Broniarczyk, Susan, and Joseph Alba. (1994) "The Importance of the Brand in Brand Extension." *Journal of Marketing Research*, 31 (May), 214–228.

Brown, Juanita J., and Albert R. Wildt. (1991) "Consideration Set Measurement." *Journal of the Academy of Marketing Science*, 20 (Summer), 235–243.

Busemeyer, Jerome R., Gerald I. Dewey, and Douglas L. Medin. (1984) "Evaluation of Exemplar-Based Generalization and the Abstraction of Categorical Information." *Journal of Experimental Psychology: Learning, Memory and Cognition*, 10 (4), 638–648.

Chakravarti, Dipankar, Deborah J. MacInnis, and Kent Nakamoto. (1990) "Product Category Perceptions, Elaborative Processing, and Brand Name Extension Strategies." In *Advances in Consumer Research*, 17, ed. M. Goldberg, G. Gorn, and R. Pollay, pp. 910–916. Provo, UT: Association for Consumer Research.

Cohen, Joel B., and Kunal Basu. (1987) "Alternative Models of Categorization: Toward a Contingent Processing Framework." *Journal of Consumer Research*, 13 (March), 455–472.

Conway, Martin A., and Debra A. Bekerian. (1987) "Situational Knowledge and Emotions." *Cognition and Emotion*, 1 (2), 145–191.

Corter, James E., and Mark A. Gluck. (1992) "Explaining Basic Categories: Feature Predictability and Information." *Psychological Bulletin*, 111 (2), 291–303.

Coupey, Eloise, and Kent Nakamoto. (1988) "Learning Context and the Development of Product Category Perceptions." In *Advances in Consumer Research*, 15, ed. Michael Houston, pp. 77–82. Provo, UT: Association for Consumer Research.

Desai, Kalpesh Kaushik, and Wayne D. Hoyer. (1993) "Line Extensions: A Categorization and An Information Processing Perspective." In *Advances in Consumer Research*, 20, ed. L. McAlister and M. Rothschild, pp. 599–606. Provo, UT: Association for Consumer Research.

———. (2000). "Descriptive Characteristics of Memory-Based Consideration Sets: Influence of Usage Occasion Frequency and Usage Location Familiarity." *Journal of Consumer Research*, 27 (December), 309–323.

Erickson, Michael A., and John K. Kruschke. (1998) "Rules and Exemplars in Category Learning." *Journal of Experimental Psychology: General*, 127 (2), 107–140.

Estes, W.K. (1986) "Memory Storage and Retrieval Processes in Category Learning." *Journal of Experimental Psychology: General*, 115 (2), 155–174.

Gentner, Dedre, (1983) "Structure-Mapping: A Theoretical Framework for Analogy." *Cognitive Science*, 7 (2), 155–170.

———. (1989) "The Mechanisms of Analogical Learning." In *Similarity and Analogical Reasoning*, ed. Stella Vosniadou and Andrew Ortony, pp. 199–241. New York: Cambridge University Press.

Gentner, Dedre, and José Medina. (1998) "Similarity and the Development of Rules." *Cognition*, 65 (2–3), 263–297.

Goldstone, Robert L. (1994) "The Role of Similarity in Categorization: Providing a Groundwork." *Cognition*, 52 (2), 125–157.

Goldstone, Robert L., Douglas Medin, and Dedre Gentner. (1991) "Relational Similarity and Nonindependence of Features in Similarity Judgments." *Cognitive Psychology*, 23 (2), 222–262.

Goodstein, Ronald C. (1993) "Category-Based Applications and Extensions in Advertising: Motivating More Extensive Ad Processing." *Journal of Consumer Research*, 20 (1), 87–99.

Gopnik, Alison, and Andrew N. Meltzoff. (1997) *Words, Thoughts and Theories.* Cambridge, MA: MIT Press.

Green, Paul E., Stephen M. Goldberg, and Mila Montemayor. (1981) "A Hybrid Utility Estimation Model for Conjoint Analysis." *Journal of Marketing*, 45 (Winter), 33–41.

Green, Paul E., and Vithala R. Rao. (1972) *Applied Multidimensional Scaling: A Comparison of Approaches and Algorithms.* New York: Holt, Rinehart, and Winston.

Gregan-Paxton, Jennifer, and Deborah Roedder John. (1997) "Consumer Learning by Analogy: A Model of Internal Knowledge Transfer." *Journal of Consumer Research*, 24 (December), 266–284.

Hair, Joe F., Rolph E. Anderson, Ronald L. Tatham, and William C. Black. (1998) *Multivariate Data Analysis*, 5th ed. Upper Saddle River, NJ: Prentice Hall.

Halstead, Diane, Thomas J. Page, and Cornelia Dröge. (1991) "Shaping Processing Mode Through Forced Focus on Attributes: From Category to Piecemeal Processing." *Proceedings of the Society for Consumer Psychology*, August 1990, pp. 27–34. Boston, MA: American Psychological Association.

Hampton, James A. (1995) "Testing the Prototype Theory of Concepts." *Journal of Memory and Language*, 34 (5), 686–708.

Holyoak, Keith J., and Paul R. Thagard. (1989) "A Computational Model of Analogical Problem Solving." In *Similarity and Analogical Reasoning*, ed. S. Vosniadou and A. Ortony, pp. 242–266. New York: Cambridge University Press.

Hong, Sung-Tai, and Robert Wyer, Jr. (1989) "Effects of Country-of-Origin and Product Attribute Information on Product Evaluation: An Information Processing Perspective." *Journal of Consumer Research*, 16 (September), 175–187.

———. (1990) "Determinants of Product Evaluation: Effects of the Time Interval Between Knowledge of a Product's Country of Origin and Information About Its Specific Attributes." *Journal of Consumer Research*, 17 (3), 277–289.

Huffman, Cynthia, and Michael J. Houston. (1993) "Goal-Oriented Experiences and the Development of Knowledge." *Journal of Consumer Research*, 20 (2), 190–207.

Hutchinson, J. Wesley, and Joseph W. Alba. (1991) "Ignoring Irrelevant Information: Situational Determinants of Consumer Learning." *Journal of Consumer Research*, 18 (3), 325–346.

Hutchinson, J. Wesley, Kalyan Raman, and Murali K. Mantrala. (1994) "Finding Choice Alternatives in Memory: Probability Models of Brand Name Recall." *Journal of Marketing Research*, 31 (4), 441–461.

Jacoby, Jacob, Jerry Olson, and Rafael Haddock. (1971) "Price, Brand Name, and Product Composition Characteristics as Determinants of Perceived Quality." *Journal of Applied Psychology*, 55 (December), 570–579.

Johnson, Eric J., and J. Edward Russo. (1984) "Product Familiarity and Learning New Information." *Journal of Consumer Research*, 11 (June), 542–550.

Johnson, Kathy E., and Carolyn B. Mervis. (1997) "Effects of Varying Levels of Expertise on the Basic Level of Categorization." *Journal of Experimental Psychology: General*, 126 (3), 248–277.

———. (1998) "Impact of Intuitive Theories on Feature Recruitment Throughout the Continuum of Expertise." *Memory and Cognition*, 26 (2), 382–401.

Johnson, Michael D. (1984) "Consumer Choice Strategies for Comparing Noncomparable Alternatives." *Journal of Consumer Research*, 11 (December), 741–753.

———. (1988) "Comparability and Hierarchical Processing in Multialternative Choice." *Journal of Consumer Research*, 15 (December), 303–314.

Johnson, Michael D., and Claes Fornell. (1987) "The Nature and Methodological Implications of the Cognitive Representation of Products." *Journal of Consumer Research*, 14 (September), 214–228.

Keil, Frank C. (1989) *Concepts*, *Kinds and Cognitive Development.* Cambridge, MA: MIT Press.

Kruschke, John K. (1992) "ALCOVE: An Exemplar-Based Connectionist Model of Category Learning." *Psychological Review*, 99 (1), 22–44.

Lamberts, Koen. (1995) "Categorization Under Time Pressure." *Journal of Experimental Psychology: General*, 124 (2), 161–80.

Loken, Barbara, and James Ward. (1990) "Alternative Approaches to Understanding the Determinants of Typicality." *Journal of Consumer Research*, 17 (September), 111–126.

Lynch, John G., and Thomas K. Srull. (1982) "Memory and Attentional Factors in Consumer Choice: Concepts and Research Methods." *Journal of Consumer Research*, 9 (June), 18–37.

Malhotra, Naresh K. (2001) "Cross-Cultural Marketing Research in the Twenty-First Century." *International Marketing Review*, 18 (3), 230–234.

———. (2004) *Marketing Research: An Applied Orientation*, 4th ed. New York: Prentice-Hall.

———. (2005) "Attitude and Affect: New Frontiers of Research in the Twenty-First Century." *Journal of Business Research*, forthcoming.

Malhotra, Naresh K., and Betsy Charles. (2002) "Overcoming the Attribute Prespecification Bias in International Marketing Research by Using Nonattribute Based Correspondence Analysis." *International Marketing Review*, 19 (1), 65–79.

Malhotra, Naresh, K., Betsy Charles, and Can Uslay. (2004) "Correspondence Analysis: Methodological Perspectives, Issues and Applications." *Review of Marketing Research*, 1, 285–316.

Malhotra, Naresh K., and Daniel McCort (2000/2001) "An Information Processing Model of Consumer Behavior: Conceptualization, Framework and Propositions." *Asian Journal of Marketing*, 8 (2), 5–32.

———. (2001) "A Cross-Cultural Comparison of Behavioral Intention Models: Theoretical Consideration and an Empirical Investigation." *International Marketing Review*, 18 (3), 235–269.

Malt, Barbara C. (1989) "An On-Line Investigation of Prototype and Exemplar Strategies in Classification."

*Journal of Experimental Psychology: Learning, Memory and Cognition*, 15 (4), 539–555.

Mandler, Jean M., Patricia J. Bauer, and Laraine McDonough. (1991) "Separating the Sheep from the Goats: Differentiating Global Categories." *Cognitive Psychology*, 23 (2), 263–298.

Markman, Arthur B., and Dedre Gentner. (2001) "Thinking." *Annual Review of Psychology*, 52 (1), 223–247.

Markman, Arthur B., and Edward Wisniewski. (1997) "Similar and Different: The Differentiation of Basic-Level Categories." *Journal of Experimental Psychology: Learning, Memory and Cognition*, 23 (January), 54–70.

Medin, Douglas L. (1989) "Concepts and Conceptual Structure." *American Psychologist*, 44, 1469–1481.

Medin, Douglas L., and John D. Coley. (1998) "Concepts and Categorization" In *Handbook of Perception and Cognition: Perception and Cognition at Century's End*, ed. J. Hochberg and J. E. Cutting, pp. 403–409. San Diego, CA: Academic Press.

Medin, Douglas L., Robert L. Goldstone, and Dedre Gentner. (1993) "Respects for Similarity." *Psychological Review*, 100 (2), 254–278.

Medin, Douglas L., Elizabeth B. Lynch, and Karen O. Solomon. (2000) "Are There Kinds of Concepts?" *Annual Review of Psychology*, 51, 121–147.

Medin, Douglas L., and Andrew Ortony. (1989) "Psychological Essentialism." In *Similarity and Analogical Reasoning*, ed. S. Vosniadou and A. Ortony, pp. 179–195. New York: Cambridge University Press.

Medin, Douglas L., and Marguerite M. Schaffer. (1978) "Context Theory of Classification Learning." *Psychological Review*, 85 (3), 207–238.

Medin, Douglas L., and Edward J. Shoben. (1988) "Context and Structure in Conceptual Combination." *Cognitive Psychology*, 20 (2), 158–190.

Medin, Douglas L., and Edward E. Smith. (1984) "Concepts and Concept Formation." *Annual Review of Psychology*, 35, 113–138.

Mervis, Carolyn B., and Maria A. Crisafi. (1982) "Order Acquisition of Subordinate-, Basic-, and Superordinate-Level Categories." *Child Development*, 53 (1), 258–266.

Mervis, Carolyn B., and Eleanor Rosch. (1981) "Categorization of Natural Objects." *Annual Review of Psychology*, 32, 89–115.

Meyers-Levy, Joan, and Alice M. Tybout. (1989) "Schema Congruity as a Basis for Product Evaluation." *Journal of Consumer Research*, 16, 39–54.

Minda, John Paul, and J. David Smith. (2001) "Prototypes in Category Learning: The Effects of Category Size, Category Structure, and Stimulus Complexity." *Journal of Experimental Psychology: Learning, Memory and Cognition*, 27 (3), 775–799.

Moreau, C. Page, Arthur B. Markman, and Donald R. Lehmann. (2001) "'What Is It?' Categorization Flexibility and Consumers' Responses to Really New Products." *Journal of Consumer Research*, 27 (March), 489–498.

Murphy, Gregory L., and Hiram H. Brownell. (1985) "Category Differentiation in Object Recognition: Typicality Constraints on the Basic Category Advantage." *Journal of Experimental Psychology: Learning, Memory and Cognition*, 11 (1), 70–84.

Murphy, Gregory L., and Douglas L. Medin. (1985) "The Role of Theories in Conceptual Coherence." *Psychological Review*, 92 (3), 289–316.

Myers, James H., and Mark I. Alpert. (1968) "Determinant Buying Attitudes: Meaning and Measurement." *Journal of Marketing*, 32 (October), 13–20.

Narayana, Chem L., and Rom J. Markin. (1975) "Consumer Behavior and Product Performance: An Alternative Conceptualization." *Journal of Marketing*, 39 (October), 1–6.

Nedungadi, Prakash. (1990) "Recall and Consumer Consideration Sets: Influencing Choice Without Altering Brand Evaluations." *Journal of Consumer Research*, 17 (3), 263–276.

Niedrich, Ronald W., Subhash Sharma, and Douglas H. Wedell. (2001) "Reference Price and Price Perceptions: A Comparison of Alternative Models." *Journal of Consumer Research*, 28 (December), 339–354.

Nosofsky, Robert M. (1986) "Attention, Similarity, and the Identification-Categorization Relationship." *Journal of Experimental Psychology: General*, 115 (1), 39–57.

———. (1988a) "Exemplar-Based Accounts of Relations Between Classification, Recognition, and Typicality." *Journal of Experimental Psychology: Learning, Memory and Cognition*, 14 (4), 700–708.

———. (1988b) "Similarity, Frequency, and Category Representations." *Journal of Experimental Psychology: Learning Memory and Cognition*, 14 (1), 54–65.

———. (1989) "Further Tests of an Exemplar-Similarity Approach to Relating Identification and Categorization." *Perception and Psychophysics*, 45 (4), 279–290.

Nosofsky, Robert M., Hyun Jung Shin, and Steven E. Clark. (1989) "Rules and Exemplars in Categorization, Identification, and Recognition." *Journal of Experimental Psychology: Learning*, *Memory and Cognition*, 15 (2), 282–304.

Nosofsky, Robert M., and Mark K. Johansen. (2000) "Exemplar-Based Accounts of 'Multiple System' Phenomena in Perceptual Categorization." *Psychonomic Bulletin and Review*, 7 (2), 375–402.

Nosofsky, Robert M., and Thomas J. Palmeri. (1998) "A Rule-Plus-Exception Model for Classifying Objects in Continuous-Dimension Spaces." *Psychonomic Bulletin and Review*, 5 (3), 345–369.

Nosofsky, Robert M., Thomas J. Palmeri, and Stephen C. McKinley. (1994) "Rule-Plus-Exception Model of Classification Learning." *Psychological Review*, 101 (1), 53–79.

Olson, Jerry C., and Jacob Jacoby. (1972) "Cue Utilization in the Quality Perception Process." In *Proceedings of the 3rd Annual Conference of the Association for Consumer Research*, ed. M. Venkatesan, pp. 167–179.

Ozanne, Julie L., Merrie Brucks, and Dhruv Grewal. (1992) "A Study of Information Search Behavior During the Categorization of New Products." *Journal of Consumer Research*, 18 (March), 452–463.

Palmeri, Thomas J., and Robert M. Nosofsky. (1995) "Recognition Memory for Exceptions to the Category Rule." *Journal of Experimental Psychology: Learning*, *Memory and Cognition*, 21 (3), 548–568.

Park, C. Whan, Sandra Milberg, and Robert Lawson. (1991) "Evaluation of Brand Extensions: The Role of Product Feature Similarity and Brand Concept Consistency." *Journal of Consumer Research*, 18 (2), 185–193.

Pechmann, Cornelia, and Srinivasan Ratneshwar. (1991) "The Use of Comparative Advertising for Brand Positioning: Association Versus Differentiation." *Journal of Consumer Research*, 18 (September), 145–160.

Ratneshwar, Srinisvasan, and Allan D. Shocker. (1991) "Substitution in Use and the Role of Usage Context in Product Category Structures." *Journal of Marketing Research*, 28 (August), 281–295.

Ratneshwar, Srinivasan, Lawrence W. Barsalou, Cornelia Pechmann, and Melissa Moore. (2001) "Goal-Derived Categories: The Role of Personal and Situational Goals in Category Representations." *Journal of Consumer Psychology*, 10 (3), 147–158.

Ratneshwar, Srinisvasan, David G. Mick, and Gail Reitinger. (1990) "Selective Attention in Consumer Information Processing: The Role of Chronically Accessible Attributes." In *Advances in Consumer Research*, 17, ed. M.E. Goldberg, G. Gorn, and R.W. Pollay, pp. 547–553. Provo, UT: Association for Consumer Research.

Ratneshwar, Srinisvasan, Cornelia Pechmann, and Allan D. Shocker. (1996) "Goal-Derived Categories and the Antecedents of Across-Category Consideration." *Journal of Consumer Research*, 23 (3), 240–250.

Richardson, Paul S., Alan S. Dick, and Arun K. Jain. (1994) "Extrinsic and Intrinsic Cue Effects on Perceptions of Store Brand Quality." *Journal of Marketing*, 58 (October), 28–36.

Rosch, Eleanor. (1975) "Cognitive Reference Points." *Cognitive Psychology*, 7 (4), 532–547.

Rosch, Eleanor, and Carolyn B. Mervis. (1975) "Family Resemblances: Studies in the Internal Structure of Categories." *Cognitive Psychology*, 7 (4), 573–605.

Rosch, Eleanor, Carolyn B. Mervis, Wayne D. Gray, David M. Johnson, and Penny Boyes-Braem. (1976) "Basic Objects in Natural Categories." *Cognitive Psychology*, 8, 382–439.

Ross, Brian H., and Gregory L. Murphy. (1999) "Food for Thought: Cross-Classification and Category Organization in a Complex Real-World Domain." *Cognitive Psychology*, 38 (4), 495–553.

Rouder, Jeffrey N., and Roger Ratcliff. (2004) "Comparing Categorization Models." *Journal of Experimental Psychology: General*, 133 (1), 63–82.

Rumelhart, David E. (1984) "Schemata and the Cognitive System." In *Handbook of Social Cognition*, 1, ed. R. Wyer and T. Srull, pp. 161–188. Hillsdale, NJ: Erlbaum.

Ruth, Julie A. (2001) "Promoting a Brand's Emotion Benefits: The Influence of Emotion Categorization Processes on Consumer Evaluations." *Journal of Consumer Psychology*, 11 (2), 99–113.

Schwarz, Norbert, and Herbert Bless. (1992) "Constructing Reality and Its Alternatives: An Inclusion/Exclusion Model of Assimilation and Contrast Effects in Social Judgment." In *The Construction of Social Judgments*, ed. L. Martin and A. Tesser, pp. 217–245. Hillsdale, NJ: Erlbaum.

Shaver, Phillip, Judith Schwarz, Donald Kirson, and Cary O'Connor. (1987) "Emotion Knowledge: Further Explanation of a Prototype Approach." *Journal of Personality and Social Psychology*, 52 (6), 1061–1086.

Shimp, Terence, Saeed Samiee, and Thomas Madden. (1993) "Countries and Their Products: A Cognitive Structure Perspective." *Journal of the Academy of Marketing Science*, 21 (4), 323–330.

Simonson, Itamar. (1989) "Choice Based on Reasons: The Case of Attraction and Compromise Effects." *Journal of Consumer Research*, 17 (September), 158–174.

Smith, Edward E., and Douglas L. Medin. (1981) *Categories and Concepts*. Cambridge: Harvard University Press.

Smith, Edward E., Douglas L. Medin, Lance J. Rips, and Margaret Keane. (1988) "Combining Prototypes: A Selective Modification Model." *Cognitive Science*, 12 (4), 485–527.

Smith, J. David. (2002) "Exemplar Theory's Predicted Typicality Gradient Can Be Tested and Disconfirmed." *Psychological Science*, 13 (5), 437–442.

Smith, J. David, and John Paul Minda. (2000) "Thirty Categorization Results in Search of a Model." *Journal of Experimental Psychology: Learning*, *Memory and Cognition*, 26 (1), 3–27.

———. (2002) "Distinguishing Prototype-Based and Exemplar-Based Processes in Dot-Pattern Category Learning." *Journal of Experimental Psychology: Learning*, *Memory and Cognition*, 28 (4), 800–811.

Smith, Linda B. (1989) "From Global Similarities to Kinds of Similarities: The Construction of Dimensions in Development." In *Similarity and Analogical Reasoning*, ed. S. Vosniadou and A. Ortony, pp. 146–178. New York: Cambridge University Press.

Snyder, Rita. (1992) "Comparative Advertising and Brand Evaluation: Toward Developing a Categorization Approach." *Journal of Consumer Psychology*, 1 (1), 15–30.

Stayman, Douglas M., Dana L. Alden, and Karen H. Smith. (1992) "Some Effects of Schematic Processing on Consumer Expectations and Disconfirmation Judgments." *Journal of Consumer Research*, 29 (September), 240–255.

Sujan, Mita. (1985) "Consumer Knowledge: Effects on Evaluation Strategies Mediating Consumer Judgments." *Journal of Consumer Research*, 12 (June), 31–46.

Sujan, Mita, and James R. Bettman. (1989) "The Effects of Brand Positioning Strategies on Consumers' Brand and Category Perceptions: Some Insights from Schema Research." *Journal of Marketing Research*, 26 (4), 454–467.

Sujan, Mita, and Christine Dekleva. (1987) "Product Categorization and Inference Making: Some Implications for Comparative Advertising." *Journal of Consumer Research*, 14 (December), 372–378.

Sujan, Mita, and Alice M. Tybout. (1988) "Applications and Extensions of Categorization Research in Consumer Behavior." In *Advances in Consumer Research*, vol. 15, ed. M. Houston, pp. 50–54, Provo, UT: Association for Consumer Research.

Szybillo, George J., and Jacoby Jacob. (1974) "Intrinsic Versus Extrinsic Cues as Determinants of Perceived Product Quality." *Journal of Applied Psychology*, 59 (February), 74–78.

Tanaka, James W., and Marjorie Taylor. (1991) "Object Categories and Expertise: Is the Basic Level in the Eye of the Beholder?" *Cognitive Psychology*, 23 (3), 457–482.

Turley, L.W., and Ronald P. LeBlanc. (1995) "Evoked Sets: A Dynamic Processing Model." *Journal of Marketing Theory and Practice*, 3 (2), 28–36.

Tversky, Amos. (1977) "Features of Similarity," *Psychological Review*, 84 (4), 327–352.

Tversky, Amos, and Itamar Gati. (1978) "Studies of Similarity." In *Cognition and Categorization*, ed. E. Rosch and B. Lloyd, pp. 79–98. Hillsdale, NJ: Erlbaum.

Vandierendock, André. (1995) "A Parallel Rule Activation and Rule Synthesis Model for Generalization in Category Learning." *Psychonomic Bulletin and Review*, 2 (4), 442–459.

Viswanathan, Madhubalan, and Terry L. Childers. (1999) "Understanding How Product Attributes Influence Product Categorization: Development and Validation of Fuzzy Set-Based Measures of Gradedness in Product Categories." *Journal of Marketing Research*, 36 (February), 75–94.

Vosniadou, Stella. (1989) "Analogical Reasoning as a Mechanism in Knowledge Acquisition: A Developmental Perspective." In *Similarity and Analogical Reasoning*, ed. S. Vosniadou and A. Ortony, pp. 413–437. New York: Cambridge University Press.

Wattenmaker, William D. (1993) "Incidental Concept Learning, Feature Frequency, and Correlated Properties." *Journal of Experimental Psychology: Learning*, *Memory and Cognition*, 19 (1), 203–222.

Yang, Lee-Xieng, and Stephan Lewandowsky. (2003) "Context-Gated Knowledge Partitioning in Categorization." *Journal of Experimental Psychology: Learning*, *Memory and Cognition*, 29 (4), 663–679.

CHAPTER 5

# INDIVIDUAL-LEVEL DETERMINANTS OF CONSUMERS' ADOPTION AND USAGE OF TECHNOLOGICAL INNOVATIONS

## A Propositional Inventory

SHUN YIN LAM AND A. PARASURAMAN

**Abstract**

*Previous studies on consumers' adoption and usage of technological innovations miss some important variables and relationships in their investigation. The purpose of this chapter is to propose an integrated framework that incorporates a more comprehensive set of various individual-level determinants of technology adoption and usage. By focusing the conceptualization on the determinants at the individual consumer level, this chapter seeks to provide an in-depth and detailed discussion of their effects. The framework serves as a starting point for a set of propositions regarding how these determinants affect adoption and usage directly and indirectly, and how some of these determinants moderate the effects of other determinants on adoption and usage of technological innovations. Based on the framework and the propositional inventory, the chapter identifies a number of critical issues worthy of further investigation and provides several implications for makers and marketers of technological innovations.*

Consumers are being exposed to new technologies at an accelerating pace. However, for various reasons, not all consumers necessarily adopt these technologies by acquiring technology-based products or subscribing to technology-based services (Mick and Fournier, 1998; Parasuraman, 2000). Furthermore, even consumers who adopt these products or services may discontinue their use after the initial trial—indeed, some of them may not attempt to use the technologies at all (Parasuraman, 2000; Rogers, 2003). Consequently, not all new technology-based products and services that are launched are successful, as illustrated by the rather limited consumer usage of mobile services (such as WAP) in some European countries (Andersson and Heinonen, 2002). Therefore, understanding the determinants of consumers' initial adoption and continued usage of technological innovations is an important research priority.

Although previous research has examined the determinants of consumers' technology adoption and usage, individual studies tend to focus on a small number of variables and relationships. As a result, some of their effects and interrelationships are not well understood. Furthermore, their effects could be complex. For example, some of the determinants may moderate or mediate the effects of the other determinants (Childers et al., 2001; Dabholkar and Bagozzi, 2002). These potentially complex relationships are yet to be explored. In this chapter, we attempt to provide a unifying conceptual framework that incorporates various individual-level determinants. These determinants concern consumer characteristics, expectations, and perceptions of individual consumers (Figure 5.1). To facilitate an in-depth examination of individual-level determinants and to keep our conceptualization manageable, we exclude from it marketing mix and social network variables. Although these external variables could affect consumers' expectations and perceptions about adopting or using technological innovations, examining their effects is beyond the scope of this chapter.

The framework we propose builds on insights from the extant research on technological innovations and extends that research in several ways. First, our framework focuses not only on the effects of the individual-level determinants of technology adoption and usage, but also on the interrelationships among the determinants. Second, we examine the impacts of the determinants on both adoption and usage and provide a comparative discussion of the two types of impacts. Third, our framework takes a longitudinal perspective—namely, that perceptions about using the focal technology at the time of adoption influence the initial usage of the technology, which, in turn, influences subsequent perceptions and hence intentions to continue usage.

On the basis of the conceptual framework, we develop a set of testable propositions and justify them by invoking both theoretical insights and related evidence from existing research. Drawing on our literature review, conceptual framework, and propositional inventory, we outline a research agenda and discuss managerial implications.

The remainder of this review is organized as follows. We begin by briefly reviewing prior research concerning consumers' adoption and usage of technology. In addition to research in the consumption context, the review also covers research conducted in organizational (or workplace) settings as some of the concepts and relationships investigated in such settings have been applied by researchers to consumption contexts. We then develop the conceptual framework and derive the propositional inventory. We conclude with a discussion of implications for further research and managerial practice.

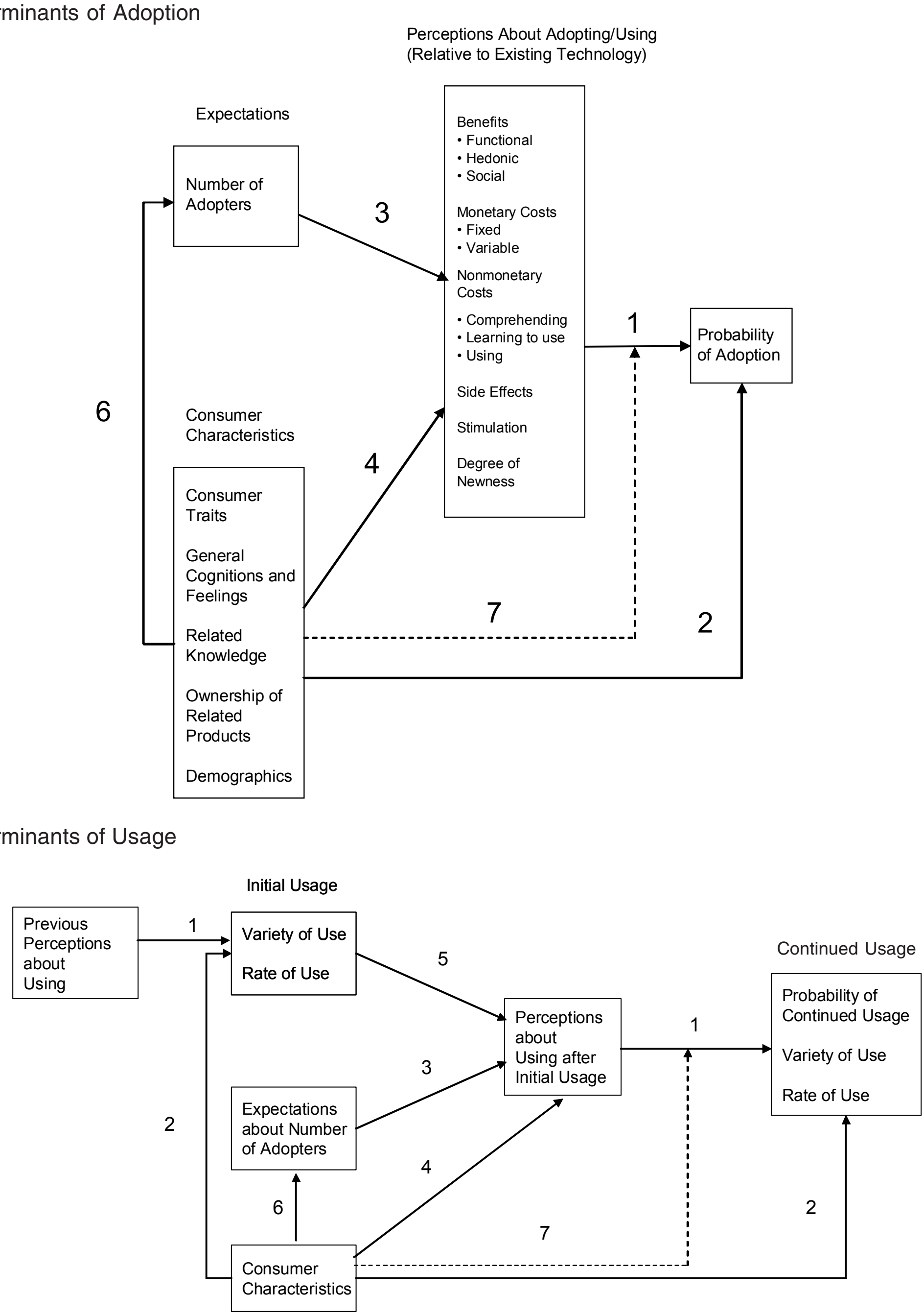
## Literature Review and Conceptual Framework

We treat technology adoption as the initial acquisition of a technology-based product (or subscription to a technology-based service) and view it as distinct from usage. Although adoption is a precondition for consumers' usage of technological innovations, and although the determinants of adoption may also influence usage, the impacts of these determinants may vary across adoption and usage (Taylor and Todd, 1995; Zhao et al., 2003). As such, adoption and usage are depicted as two distinct phenomena in our conceptual framework. Furthermore, the extant literature about innovation diffusion, adoption, and usage suggests that consumers may discontinue the use of an innovation after an initial or trial usage period (Zhao et al., 2003). Because initial usage does not guarantee continued usage, it is also meaningful to separate the two as we have done in the usage portion of Figure 5.1.

Another aspect of technology usage discussed in the literature (apart from initial versus continued usage) is variety versus rate of use (Shih and Venkatesh, 2004). *Variety of use* refers to the different ways a technology-based product or service is used. *Rate of use* refers to the time a person spends on using the product or service during a designated period—for example, the number of hours of computer use at home by an individual in a typical week. Variety and rate of technology use are conceptually distinct dimensions that, while sharing some common

Figure 5.1 **A Conceptual Framework of Consumers' Adoption and Usage of Technological Innovations**

a. Determinants of Adoption




*Note:* The numbers in the figure are the path numbers mentioned in the body of text. The broken arrows represent moderating effects.

drivers, may have some unique determinants as well (Shih and Venkatesh, 2004).

We draw on several theories about volitional behavior and information processing to develop our conceptual framework (Figure 5.1). Researchers have applied these theories to the investigation of technology adoption and usage in both the workplace and individual consumption contexts. These theories include the theory of planned behavior, theory of reasoned action, technology acceptance model (TAM), innovation diffusion theory, categorization theory, and personality theory (Ajzen, 1988; Cervone and Mischel, 2002; Sujan, 1985). In particular, there is a rich body of literature that utilizes the TAM in studying adoption and usage of technological innovations by employees or professionals in organizations (e.g., Chau and Hu 2001; Davis, 1989; Davis, Bagozzi, and Warshaw, 1989; Gefen and Straub, 1997; Venkatesh et al., 2003). The TAM highlights two kinds of perceptions as the key determinants of the adoption and usage of technological innovations. They are perceived usefulness and perceived ease of use (Davis, 1989; Venkatesh et al., 2003). Although the TAM provides a parsimonious description of the adoption and usage determinants by focusing on perceived usefulness and perceived ease of use, some researchers have attempted to provide a richer explanation of adoption and usage by invoking other relevant theories. For example, the innovation diffusion theory suggests that other perceived characteristics of innovations, such as prestige and compatibility, could also affect adoption and usage (Plouffe, Hulland, and Vandenbosch, 2001; Rogers, 2003). Previous research shows that the prediction and explanation of adoption and usage are enhanced by extending the set of determinants suggested by the TAM (Agarwal and Prasad, 1998; Plouffe, Hulland, and Vandenbosch, 2001; Venkatesh and Davis, 2000; Venkatesh et al., 2003). Therefore, we attempt to cover a broad set of relevant theories and empirical studies in our review in order to provide an integrative framework for understanding the adoption and usage of technological innovations.

Our review and synthesis of the previous research studies suggest that the determinants of consumers' adoption and usage of a technological innovation can be grouped into three sets of variables: (1) perceptions about adopting or using the innovation, (2) expectations about the number of the adopters, and (3) consumer characteristics (Figure 5.1). In addition, initial usage experience could alter consumers' perceptions concerning the innovation and consequently affect its continued usage (Taylor and Todd, 1995). The extant literature also suggests that the effects of the perceptions on adoption and usage could be mediated by consumers' attitudes and intentions toward adoption and usage (Dabholkar and Bagozzi, 2002; Davis et al., 1989). However, we exclude these variables in order to stay focused on the three sets of determinants—perceptions, expectations, and consumer characteristics—and to keep the development of our propositions manageable.

As Figure 5.1 shows, the relationships in our framework can be divided into several types: the antecedents of adoption and usage (paths 1–2), the antecedents of perceptions (paths 3–5), the relationships between consumer characteristics and expectations (path 6), and the moderating role of consumer characteristics (path 7). Our review shows that many of the relationships in our framework have neither been empirically tested nor otherwise adequately examined in previous research. In the following sections, we formulate these relationships as propositions, and we provide theoretical arguments and relevant evidence for the propositions. Table 5.1 provides a summary of the propositions and the related literature. As many of the relationships are similar for both adoption and usage (Figure 5.1), we discuss them together. However, where warranted, we also postulate possible differences in the effects of the determinants between the adoption and usage stages.

Table 5.1

**Propositional Inventory**

| Path | Relationship | No.[a] | Propositions | Related literature |
|---|---|---|---|---|
| 1 | Antecedents of adoption and usage: perceptions | 1 | The perceived benefits (functional, hedonic, social) of adopting and/or using a technological innovation have positive effects on the probability that a consumer adopts the innovation | Childers et al. (2001); Dabholkar and Bagozzi (2002); Davis et al. (1989); Gefen et al. (2003a); Moore and Benbasat (1991); Rogers (2003) |
| | | 2 | The perceived benefits (functional, hedonic, social) of using a technological innovation have positive effects on the initial usage (variety and rate) and continued usage (probability, variety, and rate) of the innovation | Agarwal and Karahanna (2000); Childers et al. (2001); Dabholkar and Bagozzi (2002); Davis et al. (1989); Rogers (2003) |
| | | 3 | The perceived functional benefits of using a technological innovation have stronger effects on consumers' continued usage of the innovation (probability, variety and rate of use) than on the probability of adoption | Gefen et al. (2003b); Taylor and Todd (1995) |
| | | 4 | The perceived social prestige associated with adopting a technological innovation has stronger effects on adoption and usage in the introductory and growth stages of its life cycle than in the maturity stage | Bearden et al. (1989); Fisher and Price (1992); Gatignon and Robertson (1985); Rogers (2003); Venkatesh and Brown (2001) |
| | | 5 | The perceived social approval benefit associated with adopting a technological innovation has stronger effects on adoption and usage in the maturity stage of its life cycle than in the introductory and growth stages | Bearden et al. (1989); Fisher and Price (1992); Gatignon and Robertson (1985); Karahanna et al. (1999); Rogers (2003); Venkatesh and Morris (2000); Venkatesh et al. (2003) |
| | | 6 | The perceived acquisition and variable usage costs of a technological innovation have negative effects on the probability of its adoption | Parasuraman (2000); Rogers (2003) |
| | | 7 | The perceived variable usage costs of a technological innovation at the time of adoption have negative effects on the innovation's initial rate of use | Parasuraman (2000); Rogers (2003) |

*(continued)*

Table 5.1 *(continued)*

| Path | Relationship | No.[a] | Propositions | Related literature |
|---|---|---|---|---|
| | | 8 | The perceived variable usage costs of a technological innovation after initial usage have negative effects on the probability and rate of the innovation's continued usage | Parasuraman (2000); Rogers (2003) |
| | | 9 | The perceived difficulties of comprehending, learning to use, and using a technological innovation have negative effects on its probability of adoption | Bruner and Kumar (2004); Childers et al. (2001); Dabholkar and Bagozzi (2002); Gefen et al. (2003); Rogers (2003); Venkatesh (2000) |
| | | 10 | The perceived difficulties of learning to use and using a technological innovation have negative effects on its initial usage (variety and rate) and continued usage (probability, variety, and rate) | Bruner and Kumar (2004); Childers et al. (2001); Dabholkar and Bagozzi (2002); Gefen et al. (2003); Rogers (2003); Venkatesh (2000) |
| | | 11 | The perceived side effects of using a technological innovation have negative effects on its probability of adoption | Burroughs and Sabherwal 2001; Parasuraman 2000; Zeithaml and Gilly 1987) |
| | | 12 | The perceived side effects of using a technological innovation at the time of adoption have negative effects on its initial usage (variety and rate) and continued usage (probability, variety, and rate) | Burroughs and Sabherwal 2001; Parasuraman 2000; Zeithaml and Gilly 1987 |
| | | 13 | The perceived stimulation provided by a technological innovation affects its probability of adoption. Furthermore, this relationship is in the form of an inverted U-shaped curve | Baumgartner and Steenkamp (1996); Raju (1980); Steenkamp and Baumgartner (1995) |
| | | 14 | The perceived stimulation provided by a technological innovation affects its initial usage (variety and rate of initial use) and continued usage (probability, variety, and rate of continued use). Furthermore, these relationships are in the form of inverted U-shaped curves | Baumgartner and Steenkamp (1996); Raju (1980); Steenkamp and Baumgartner (1995) |
| | | 15 | The perceived degree of newness of a technological innovation has a positive effect on the perceived stimulation delivered by the innovation | Ashcraft (1989); Raju (1980) |

| | | | | |
|---|---|---|---|---|
| | | 16 | The perceived degree of newness of a technological innovation has a positive effect on the perceived costs in comprehending, learning to use, and using the innovation | Ashcraft (1989); Goldenberg et al. (2001) |
| 2 | Antecedents of adoption and usage: consumer characteristics | 17 | Consumer traits (such as innovativeness and impulsivity) have direct effects on adoption and initial usage of a technological innovation | Bargh et al. (1996); Hirschman (1980); Petty and Cacioppo (1996); Rook (1987) |
| | | 18 | The direct effects of consumer traits on continued usage of a technological innovation are weaker than their effects on the innovation's adoption and initial usage | Gefen et al. (2003a); Taylor and Todd (1995) |
| | | 19 | The general cognitions and feelings that consumers have about technology affect their probability of adoption, initial usage (variety and rate), and continued usage (probability, variety, and rate) of a technological innovation | Bargh et al. (1996); Fiske (1982); Mick and Fournier (1998); Parasuraman (2000); Sujan (1985) |
| | | 20 | The effects of consumers' general cognitions and feelings on continued usage of a technological innovation are weaker than their effects on adoption and initial usage | Bargh et al. (1996); Fiske (1982); Mick and Fournier (1998); Parasuraman (2000); Sujan (1985); Taylor and Todd (1995) |
| 3–5 | Antecedents of perceptions | 21 | Consumers' expectations about the number of people who have already adopted a technological innovation have a positive effect on their perceived functional benefits in using the innovation | Hirschman (1980); Parasuraman and Colby (2001); Shankar and Bayus (2002); Rogers (2003) |
| | | 22 | Consumers' expectations about the number of people who will adopt a technological innovation in the future have a positive effect on their perceived functional benefits in using the innovation | Hirschman (1980); Parasuraman and Colby (2001); Rogers (2003); Shankar and Bayus (2002) |
| | | 23 | Consumers' expectations about the number of people who have already adopted the innovation have a positive effect on their perceived social approval benefits of adopting the innovation | Shankar and Bayus (2002); Parasuraman and Colby (2001) |

*(continued)*

Table 5.1 *(continued)*

| Path | Relationship | No.[a] | Propositions | Related literature |
|---|---|---|---|---|
| | | 24 | Consumers' expectations about the number of people who will adopt the innovation in the future have a positive effect on their perceived social approval benefits of adopting the innovation | Shankar and Bayus (2002); Parasuraman and Colby (2001) |
| | | 25 | Consumers' expectations about the number of people who have already adopted the innovation have a negative effect on their perceived social prestige associated with adopting the innovation | Rogers (2003) |
| | | 26 | Consumers' expectations about the number of people who will adopt the innovation in the future have a negative effect on their perceived social prestige associated with adopting the innovation | Rogers (2003) |
| | | 27 | Consumers' perceptions about adopting or using a technological innovation will be influenced by certain consumer traits | Bruner and Kumar (2004); Fiske (1982); Sujan (1985) |
| | | 28 | Consumers' perceptions about adopting or using a technological innovation will be influenced by their general cognitions and feelings about technology | Bruner and Kumar (2004); Fiske (1982); Sujan (1985) |
| | | 29 | Consumer knowledge has a positive effect on the perceived functional benefits of using a technological innovation when the knowledge relates to the core technology underlying the innovation | Moreau et al. (2001) |
| | | 30 | Consumer knowledge has no effect, or a negative effect, on the perceived functional benefits of using a technological innovation when the knowledge is unrelated to the core technology underlying the innovation | Moreau et al. (2001) |
| | | 31 | Ownership of complementary products has positive effects on the perceived benefits of adopting or using a technological innovation | Russell et al. (1997); Shocker, Bayus, and Kim (2004) |

| | | | | |
|---|---|---|---|---|
| | | 32 | Ownership of substitutable products increases the perceived monetary costs of adopting or using a technological innovation | Russell et al. (1997); Shocker, Bayus, and Kim (2004) |
| | | 33 | Initial usage of a technological innovation (variety and rate) has a positive effect on the perceived functional benefits of using the innovation | Shih and Venkatesh (2004) |
| 6 | Relationships between expectations and consumer characteristics | 34 | Consumer characteristics (e.g., optimism about technology and occupation) affect consumers' expectations about the number of adopters and usage (rate and variety) of a technological innovation | Parasuraman (2000) |
| 7 | Moderating role of consumer characteristics | 35 | Consumer characteristics (e.g., frugality, impulsivity, income, and gender) moderate the effects of consumers' perceptions (e.g., about benefits and costs) on adoption and usage of a technological innovation | Lastovicka et al. (1999); Rook (1987); Rook and Fisher (1995); Venkatesh and Morris (2000) |

[a] This is the proposition number stated in the body of the text.

## Propositional Inventory

### *Antecedents of Adoption and Usage: Perceptions (Path 1)*

Using the theory of reasoned action or the theory of planned behavior as a theoretical backdrop (Ajzen, 1988; Ajzen and Fishbein, 1980; Sujan, 1985), previous studies have consistently found that perceived usefulness and ease of use of a technological innovation positively affect employees' usage of the innovation in organizations (Agarwal and Prasad, 1999; Davis et al., 1989). Applying the conceptualizations in these studies to consumer settings, other researchers have found support for the influences of perceived usefulness (or similar concepts) and ease of use on consumers' adoption and usage of technological innovations (Bruner and Kumar, 2005; Childers et al., 2001). Furthermore, some researchers have extended their investigation to other perceptions that consumers may form about an innovation, such as perceived enjoyment and fun, and found support for the influences of these perceptions (Childers et al., 2001; Dabholkar and Bagozzi, 2002).

On the basis of our literature review, we broaden the set of perceptual antecedents of adoption and usage of a technological innovation. Our expanded set includes a variety of perceived benefits, costs, and risks. Furthermore, we postulate that consumers take a "relative" perspective in forming these perceptions—that is, they compare the innovation with currently available products or services that are meant for accomplishing the same or a similar purpose as that of the innovation. The idea that the perceptions are framed in relative terms is consistent with the notion of relative advantage advanced by Rogers (2003) in his seminal work about innovation diffusion. Relative advantage is the degree to which an innovation is perceived as being better than the idea it supersedes (Rogers, 2003). For example, in considering whether to adopt third-generation (3G) mobile communication services, consumers may form their perceptions about such services by comparing the costs and benefits of 3G services with those of the services they are currently using (such as 2G services). Dabholkar (1994) provides evidence that consumers' usage of an innovative self-service option—touch-screen ordering—is influenced by their perceptual comparison of the option with a conventional verbal ordering option. Therefore, we treat perceptual antecedents of adoption and usage in our framework as perceptions about an innovation relative to those about existing products or services satisfying the same or similar needs. However, for simplicity, we just use the term *perceptions* to denote the relative perceptions in the propositions.

#### *Perceived Benefits*

Whereas perceived usefulness concerns the functional benefits that consumers obtain from using an innovation (Davis et al., 1989), they may also derive certain benefits that are not related to task accomplishment or problem solving (Childers et al., 2001; Rogers, 2003). These benefits include hedonic benefits (fun, excitement, enjoyment, aesthetic value, etc.) and social benefits (social prestige and approval) (Agarwal and Karahanna, 2000; Moore and Benbasat, 1991; Rogers, 2003). Many of these benefits pertain to usage, but some may be principal drivers of just adoption. For example, mere possession of an innovative product may bestow prestige on the product's owner. Similarly, consumers may derive other benefits from a product without actually using it. For instance, without turning a cellular phone on, a consumer might admire and derive pleasure from the visual aesthetics of the phone's design. Therefore, although both adoption and usage of an innovation could be affected by the perceived benefits of using the innovation, adoption could also be influenced by the perceived benefits of merely adopting (possessing) the innovation. This is usually an antecedent of perceived usefulness but is significant in its own right when the benefits relate directly to the technology.

Although some of the benefits (such as perceived usefulness, fun, and enjoyment) have been well investigated in previous studies (Childers et al., 2001; Dabholkar and Bagozzi, 2002; Gefen et al., 2003b), other benefits (notably social prestige and aesthetic benefits) have not. We postulate that these benefits (functional, hedonic, or social) have positive effects on the adoption of a technological innovation.

P1: The perceived benefits (functional, hedonic, social) of adopting and/or using a technological innovation have positive effects on the probability that a consumer adopts the innovation.

Similarly, because the perceived benefits of using a technological innovation relate to the utility of using the innovation in various ways, these benefits will have positive effects on initial usage and continued usage.

P2: The perceived benefits (functional, hedonic, social) of using a technological innovation have positive effects on the initial usage (variety and rate) and continued usage (probability, variety and rate) of the innovation.

Consumers will feel more certain or confident about their perceptions of benefits after usage (Taylor and Todd, 1995). This would be particularly so for the perceived functional benefits, some of which may become apparent only after initial usage. Therefore, perceived functional benefits would have stronger effects on continued usage than on adoption.

P3: The perceived functional benefits of using a technological innovation have stronger effects on consumers' continued usage of the innovation (probability, variety, and rate of use) than on the probability of adoption.

The social benefits construct consists of social prestige and social approval benefits. The effects of the two types of social benefits may manifest themselves in different stages of an innovation's product life cycle. Social prestige concerns the status conveyed by an innovation to its adopter (Fisher and Price, 1992; Rogers, 2003). It relates to a person's desire to enhance his or her social status through using products or services that are uncommon and signify status. For example, analog mobile phones were considered a status symbol when they were first introduced in the 1980s (Rogers, 2003). Venkatesh and Brown (2001) also noticed the role of status in the adoption of a technology. In their investigation about adoption of personal computers at home, Venkatesh and Brown asked a sample of personal computer adopters to describe the factors contributing to their purchase of personal computers. The majority of them mentioned gain in social status as a factor leading to their purchase. On the other hand, social approval concerns a person's desire to be connected with or admitted into a social group by conforming to the norms of that group (Bearden et al., 1989; Gatignon and Robertson, 1985). Previous research in user acceptance of technological innovations in the workplace provides support for the positive effect of social approval (subjective norms) on the adoption and usage of a technological innovation (Karahanna et al., 1999; Venkatesh and Morris, 2000; Venkatesh et al., 2003). Accordingly, social prestige would be a more important concern in the introductory and growth stages of the innovation's life cycle when the limited adoption of the innovation in a society imbues early adopters with a sense of prestige. In contrast, social approval would be a more influential determinant in the maturity stage of the cycle when adopting or using the innovation has become a norm in the social group concerned. Therefore,

P4: The perceived social prestige associated with adopting a technological innovation has stronger effects on adoption and usage in the introductory and growth stages of its life cycle than in the maturity stage.

P5: The perceived social approval benefit associated with adopting a technological innovation has stronger effects on adoption and usage in the maturity stage of its life cycle than in the introductory and growth stages.

*Perceived Costs and Risks*

Although consumers obtain various kinds of benefits from using a technological innovation, often they also incur some costs and risks (Parasuraman, 2000). The costs may include both monetary and nonmonetary costs. The monetary costs consist of acquisition costs and variable usage costs. For example, to use mobile communication services, a consumer may need to purchase a cellular phone and to subscribe to a tariff plan. A typical tariff plan consists of a fixed service charge and a variable charge that depends on the amount of mobile service usage. The purchase cost of the phone and the fixed service charge constitute the acquisition costs, whereas the variable service charge and other usage-dependent costs (e.g., the cost of charging the phone's battery) constitute the variable costs. When deciding whether to adopt a technological innovation, consumers are likely to take into account both the acquisition and the variable usage costs. When using the innovation, they are likely to focus on the variable usage costs. Furthermore, in the usage stage, the variable costs may mainly affect the rate of use rather than variety of usage, since the usage charge is usually not linked to the latter.

Therefore, we posit:

P6: The perceived acquisition and variable usage costs of a technological innovation have negative effects on the probability of its adoption.

P7: The perceived variable usage costs of a technological innovation at the time of adoption have negative effects on the innovation's initial rate of use.

P8: The perceived variable usage costs of a technological innovation after initial usage have negative effects on the probability and rate of the innovation's continued usage.

Often the adoption and usage of a technological innovation involve nonmonetary costs (time and effort) in addition to monetary costs. Past research has found that perceived ease of use has a positive effect on consumers' adoption and use of technological innovations (Dabholkar and Bagozzi, 2002; Gefen et al., 2003). The ease of use concept can be considered as the opposite of the effort required to use the innovation and is negatively related to the complexity concept proposed by Rogers (2003). Rogers defines complexity as the degree to which an innovation is perceived to be difficult to understand and use. Accordingly, the ease (or difficulty) pertains not only to the actual use but also to understanding what an innovation is about and learning to use it. Thus, consumers might consider three kinds of nonmonetary costs in making decisions about adopting and using an innovation: (1) the cost of comprehending what the innovation is about, (2) the cost of learning to use the innovation (e.g., time and effort spent on reading the manual of a technology-based product), and (3) the cost of actually using the innovation.

Although consumers may take into account all three types of nonmonetary costs in deciding whether to adopt a technological innovation, in the usage stage, they may focus only on the latter two types (i.e., nonmonetary costs associated with learning to use and actually using the innovation). Whereas previous studies have examined the effects of various nonmonetary costs on consumers' usage of technological innovations (Childers et al., 2001; Dabholkar and Bagozzi, 2002; Bruner and Kumar, 2004), they generally do not distinguish among the different types of nonmonetary costs and their differential effects. These studies either treat the different types of costs as reflective indicators of the "ease of use" construct or focus just on the time and effort costs of actually using an innovation. For some innovations, consumers may have different perceptions about the three kinds of costs. For example, it may be time consuming for some consumers to learn to use digital cameras because of unfamiliarity with these types of cameras. However, operating them may seem easy after consumers start using them—particularly when the consumers just need to use the basic functions. Therefore, it is meaningful and desirable to separate the three kinds of costs in examining their differential impacts on adoption and usage.

P9: The perceived difficulties of comprehending, learning to use, and using a technological innovation have negative effects on its probability of adoption.

P10: The perceived difficulties of learning to use and using a technological innovation have negative effects on its initial usage (variety and rate) and continued usage (probability, variety, and rate).

The existing literature suggests that using a technological innovation can lead to certain side effects (Burroughs and Sabherwal, 2001; Parasuraman, 2000; Zeithaml and Gilly, 1987). These are the unintended consequences that are, or may be perceived as, hazardous to consumers. For example, some research suggests that regularly carrying and using cellular phones may lead to reduced fertility in males due to the radiation emitted by these phones (Leake, 2004). Previous research has also examined other types of side effects such as the loss of privacy in the use of the Internet. Overall, however, the influences of perceived side effects on technology adoption and use have not been comprehensively or formally explored in the existing literature.

P11: The perceived side effects of using a technological innovation have negative effects on its probability of adoption.

P12: The perceived side effects of using a technological innovation have negative effects on its initial usage (variety and rate) and continued usage (probability, variety and rate).

*Perceived Stimulation and Degree of Newness*

A technological innovation could provide consumers with both sensory and cognitive stimulation (Baumgartner and Steenkamp, 1996). For example, advanced LCD displays might offer strong visual sensation, whereas advanced digital cameras might trigger cognitive stimulation because of their superb programming ability to suit different lighting conditions. Previous studies in psychology and consumer research have found that humans have optimal stimulation levels—they prefer stimulation up to a certain point, beyond which they do not favor additional increase in stimulation (Raju, 1980; Steenkamp and Baumgartner, 1995). Therefore, we expect that the relationship between perceived stimulation and adoption/usage is in the form of an inverted U-shaped curve.

P13: The perceived stimulation provided by a technological innovation affects its probability of adoption. Furthermore, this relationship is in the form of an inverted U-shaped curve.

P14: The perceived stimulation provided by a technological innovation affects its initial usage (variety and rate of initial use) and continued usage (probability, variety and rate of continued use). Furthermore, these relationships are in the form of inverted U-shaped curves.

When consumers encounter an innovation, they may form an impression about the degree to which it is truly novel. They may form this impression rapidly through a global comparison of an arbitrarily selected subset of features of the innovation and the product category in which the technology marketer positions the innovation (Ashcraft, 1989). This perceived degree of newness of the innovation may influence its adoption and usage through two different pathways. On the one hand, the perceived overall degree of newness can be expected to positively affect perceived stimulation, which, in turn, will influence adoption and usage in a curvilinear fashion (P13 and P14). On the other hand, the perceived degree of newness might also trigger perceptions of higher nonmonetary costs (i.e., time and effort needed to comprehend and use the innovation) (Goldenberg, Lehmann, and Mazursky, 2001), which, in turn, will have negative effects on adoption and usage (P9 and P10). The following two propositions reflect the immediate consequences of degree of newness.

P15: The perceived degree of newness of a technological innovation has a positive effect on the perceived stimulation delivered by the innovation.

P16: The perceived degree of newness of a technological innovation has a positive effect on the perceived costs in comprehending, learning to use, and using the innovation.

As Figure 5.2 shows, however, the two pathways from perceived degree of newness of an innovation can have potentially counteracting effects on the innovation's adoption and usage. Therefore, the total effect of degree of newness on adoption and usage will be complex and hence is an empirical question.

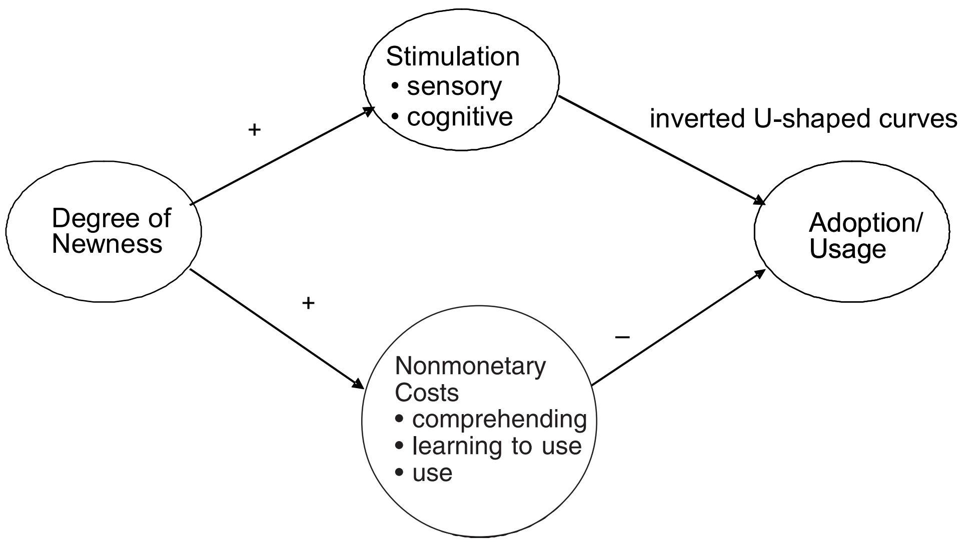
### *Antecedents of Adoption and Usage: Consumer Characteristics (Path 2)*

Among the various antecedents included under consumer characteristics in our conceptual framework (Figure 5.1), two sets of antecedents might directly affect adoption and usage of a technological innovation (path 2). These antecedent sets are consumer traits, and general cognitions and feelings about technology.

#### *Consumer Traits*

Research on concept activation and automaticity of behavior shows that behavioral responses to situations could be represented mentally (Bargh et al., 1996). For example, consumers with high

Figure 5.2 **Effects of Degree of Newness on Stimulation, Nonmonetary Costs, and Consumers' Adoption and Usage of Technological Innovations**




innovativeness may exhibit a general tendency to react favorably toward new products (Hirschman, 1980). Similarly, consumers with high impulsivity may be positively disposed toward situations that offer them immediate rewards or even merely signal to them the availability of immediate rewards (Rook, 1987). Thus, certain features associated with a situation may directly trigger behavioral responses from some types of consumers without necessarily affecting the consumers' perceptions or judgments about the situation. In consumption contexts, technological innovations may act as conditioned reinforcers that imply to consumers the availability of certain benefits (functional, hedonic, or social). In other words, merely characterizing a product or service as a technological innovation might increase the propensity of highly innovative or impulsive consumers to adopt or use it without elaborating on its merits. In making adoption and initial usage decisions, these consumers may rely entirely on peripheral cues and heuristics rather than elaborating on the attributes of the innovation (Petty and Cacioppo, 1986). Therefore, impulsivity and innovativeness can be expected to have significant direct relationships with adoption and initial usage of a technological innovation.

P17: Consumer traits (such as innovativeness and impulsivity) have direct effects on adoption and initial usage of a technological innovation.

After initial usage, perceptions about using the innovation are likely to become more salient in consumers' minds (Taylor and Todd, 1995). In addition, consumers would feel more confident about their perceptions as they develop a better understanding of the attribute-benefit linkages through increased usage. Therefore, their behavioral responses toward the innovation would be preceded by more extensive mental elaboration, thereby diminishing the direct influence of consumer traits on continued usage of the innovation.

P18: The direct effects of consumer traits on continued usage of a technological innovation are weaker than their effects on the innovation's adoption and initial usage.

### *General Cognitions and Feelings About Technology*

It is well known that consumers classify products into general categories (e.g., "Japanese-made cars") and invoke prior cognitions and feelings about those categories in evaluating specific new products (Fiske, 1982; Sujan, 1985). Past research on technological innovations also provides evidence that consumers group technology-based products and services into a broad "technology" category and have general cognitions and feelings about this category (Mick and Fournier, 1998; Parasuraman, 2000). In his research focusing on consumers' readiness to adopt and use technology, Parasuraman (2000) found that their "technology readiness" consisted of four distinct components: *innovativeness*, *optimism*, *discomfort*, and *insecurity.* Innovativeness represents an inherent tendency to acquire technology-based products and services, and to gather and share information about them. As such, it is akin to a consumer trait. The other three components represent consumers' general cognitions and feelings about technology. Parasuraman developed a multiple-item, four-dimensional (corresponding to the four components) scale called the technology readiness index (TRI) for measuring consumers' overall technology readiness. He found that consumers' TRI scores correlated well with their adoption and usage of a variety of technology-based products and services. However, his study did not investigate whether the influences of general cognitions and feelings on adoption and usage are direct or mediated by perceptions. Findings from previous studies on concept activation suggest that when a stereotype ("technology" in our case) is primed subliminally, the content of the stereotype affects behavior directly rather than through perceptions (Bargh et al., 1996). Consequently, we postulate:

P19: The general cognitions and feelings that consumers have about technology affect their probability of adoption, initial usage (variety and rate), and continued usage (probability, variety, and rate) of a technological innovation.

Moreover, based on arguments similar to those in the preceding section ("Consumer Traits"), after initial usage of a technological innovation, consumers may rely more on their perceptions about the innovation in deciding whether to continue using it. Therefore,

P20: The effects of consumers' general cognitions and feelings on continued usage of a technological innovation are weaker than their effects on adoption and initial usage.

## ***Antecedents of Perceptions (Paths 3–5)***

These antecedents include consumers' expectations and consumer characteristics (paths 3–4). In addition, initial usage experience may also affect perceptions that serve as antecedents of continued usage (path 5).

### *Expectations About the Number of Adopters*

Consumers' expectations (or estimates) about the number of adopters of an innovation could influence their perceptions about the benefits associated with the innovation. Shankar and Bayus (2002) discuss various benefits due to an increase in the number of adopters ("network effects").

Direct benefits include a higher utilization rate of the product or service when the utilization involves data transmission between users—as in the case of cellular phones, videocassette recorders, or computer software. Indirect benefits include: (1) sharing of experience between users, (2) increased availability of complementary products or services, and (3) social benefit due to identification with the product or service. Prominent examples of products that have these indirect benefits include computer hardware and software, video games, and so on. Furthermore, consumers may treat "trials by other consumers" as their vicarious trials of a technological innovation (Hirschman, 1980). Consequently, if they expect that many consumers have already adopted an innovation, the functional benefits they perceive in the innovation will increase. On the basis of the foregoing arguments, we posit:

P21: Consumers' expectations about the number of people who have already adopted a technological innovation have a positive effect on their perceived functional benefits in using the innovation.

In addition, consumers' expectations about the number of people who *will* adopt the innovation in the future may also affect their perceptions (Parasuraman and Colby, 2001). For example, for emerging telecommunication products such as video phones, a consumer's perceptions of the benefits of using them would depend on the number of other consumers, with whom the consumer might communicate, who would also have video phones. Therefore, if the consumer expects that many consumers will adopt an innovation in the near future, he or she will perceive more functional utility in that innovation. Therefore, we hypothesize:

P22: Consumers' expectations about the number of people who will adopt a technological innovation in the future have a positive effect on their perceived functional benefits in using the innovation.

Consumers' expectations about the number of people who have adopted or will adopt it in the future may also positively affect their perceived social approval benefits of adopting or using it (Shankar and Bayus, 2002). As the number of adopters increases, the adoption or usage of the innovation concerned will become a symbol of social identity and hence could bring to the adopters or users the benefits of social approval. However, increased adoption or usage may decrease the perceived social prestige benefits because the innovation will no longer be rare or distinctive and hence will lose its status-conveying ability as the number of adopters increases. Based on the preceding arguments, we posit:

P23: Consumers' expectations about the number of people who have already adopted the innovation have a positive effect on their perceived social approval benefits of adopting the innovation.

P24: Consumers' expectations about the number of people who will adopt the innovation in the future have a positive effect on their perceived social approval benefits of adopting the innovation.

P25: Consumers' expectations about the number of people who have already adopted the innovation have a negative effect on their perceived social prestige associated with adopting the innovation.

P26: Consumers' expectations about the number of people who will adopt the innovation in the future have a negative effect on their perceived social prestige associated with adopting the innovation.

*Consumer Characteristics*

Certain consumer traits may have positive effects on perceptions about adopting or using a technological innovation. For example, Bruner and Kumar (2004) found that consumers' perceived usefulness and ease of use of handheld Internet devices are positively related to their visual orientation (a trait factor). The general cognitions and feelings about technology may also affect consumers' evaluations of the innovation and hence their perceptions (Fiske, 1982; Sujan, 1985). For example, consumers with high optimism about technology may perceive higher functional benefits than may consumers with low optimism. Identifying exhaustive lists of specific consumer traits and cognitions/feelings that might influence consumers' perceptions is beyond the scope of this chapter. As such, we propose the following global propositions as a starting point for more in-depth examination in future research.

P27: Consumers' perceptions about adopting or using a technological innovation will be influenced by certain consumer traits.

P28: Consumers' perceptions about adopting or using a technological innovation will be influenced by their general cognitions and feelings about technology.

Knowledge related to a technological innovation could affect consumers' comprehension and hence their perceptions about adopting or using the innovation. However, the effect may not always be positive (Moreau et al., 2001). Moreau et al. investigated how knowledge affects consumers' comprehension of digital cameras and showed that consumers with high expertise in film-based cameras find it more difficult to understand digital cameras than are novice consumers with little expertise in film-based cameras. Moreau et al. explained this intriguing finding by suggesting that while the experts discern more differences between digital and film-based camera than novices, their knowledge about film-based cameras (e.g., in-depth understanding of film technology) makes it hard for them to cope with those differences. As a result, their entrenched knowledge creates more difficulties for them in understanding the innovation (digital cameras). Therefore,

P29: Consumer knowledge has a positive effect on the perceived functional benefits of using a technological innovation when the knowledge relates to the core technology underlying the innovation.

However,

P30: Consumer knowledge has no effect, or a negative effect, on the perceived functional benefits of using a technological innovation when the knowledge is unrelated to the core technology underlying the innovation.

Ownership of complementary products may have positive effects on the perceived benefits of adopting or using a technological innovation because when the innovation is used together with the complementary products, the perceived benefits of the innovation could be enhanced (Russell et al., 1997; Shocker, Bayus, and Kim 2004). Conversely, ownership of substitutable products may increase the perceived monetary costs of adopting or using a technological innovation (relative to the costs of continuing to use existing products serving the same needs). The presence of the substitutable products would magnify the relative cost perception because consumers would have to forgo the substitutable products and the accessories of those products if they started using the innovation.

P31: Ownership of complementary products has positive effects on the perceived benefits of adopting or using a technological innovation.

P32: Ownership of substitutable products increases the perceived monetary costs of adopting or using a technological innovation.

Demographics may also affect the perceived benefits of adopting or using a technological innovation. For example, age may affect the perceived benefits because the information-processing ability of consumers varies with age (Morris and Venkatesh, 2000). Income would affect price sensitivity and hence the perceived monetary costs of adopting and using the innovation (Burroughs and Sabherwal, 2001). Other demographic variables, such as gender and educational level, may correlate with or be proxies for related knowledge (Agarwal and Prasad, 1999). Therefore, their observed main effects on perceptions might become negligible after taking into account the effects of related knowledge on perceptions. Consequently, we do not state their effects formally as propositions. However, we suggest that demographics be included as control variables to adjust for any unobserved heterogeneity among consumers when researchers want to examine the effects of other variables on consumers' adoption or usage of a technological usage.

*Initial Usage Experience*

As noted in an earlier section discussing the influences of perceived benefits on adoption and usage, some of the functional benefits of a technological innovation may only be realized or confirmed after consumers have started using the innovation. The more frequently consumers use the innovation, the more uses or applications of the innovation they may discover (Shih and Venkatesh, 2004). Therefore, the rate of initial usage would have a positive effect on perceived functional benefits, which subsequently influence continued usage. Similarly, if a consumer has tried the innovation in many different types of usage situations, he or she would be more likely to appreciate the functional benefits of the innovation. Therefore,

P33: Initial usage of a technological innovation (variety and rate) has a positive effect on the perceived functional benefits of using the innovation.

***Relationships Between Consumer Characteristics and Expectations (Path 6)***

Certain consumer characteristics could affect the expectations about the number of adopters. For example, consumers who are generally optimistic about technology are likely to have higher expectations for the number of adopters than are less optimistic consumers. Consumers who work in technology-related professions may also differ from those who do not in terms of their expectations about the number of adopters. Therefore, at a general level, P34: Consumer characteristics (e.g., optimism about technology and occupation) affect consumers' expectations about the number of adopters of a technological innovation.

### *Moderating Role of Consumer Characteristics (Path 7)*

Consumer characteristics such as consumer traits and demographics may moderate the effects of perceptions on adoption and usage of a technological innovation. For example, frugal consumers may be particularly sensitive to functional benefits because they are more interested in the long-term outcomes of using their resources than are other consumers (Lastovicka et al., 1999). Therefore, the effects of perceived functional benefits on adoption and usage would be stronger for consumers with high frugality than for consumers with low frugality. In contrast, impulsive consumers are more sensitive to hedonic benefits than are other consumers because these benefits can often be felt as soon as consumers adopt or start using an innovation (Rook, 1987; Rook and Fisher, 1995). For example, by incorporating the state-of-the-art LCD display technology, an advanced laptop could provide consumers with substantial aesthetic benefits, which can be immediately appreciated by the consumers. Consequently, we expect that the effects of perceived hedonic benefits on adoption and usage would be stronger for consumers with high impulsivity than for consumers with low impulsivity. Moreover, the effects of perceived nonmonetary costs on adoption and usage may be moderated by income since income may affect the opportunity cost of time. Therefore, the effects of the perceived nonmonetary costs spent on comprehending, learning to use, and using a technological innovation would be stronger for consumers with high incomes than for consumers with low incomes. Finally, gender may moderate the effect of social benefits on adoption or usage. Previous research done in the workplace provides evidence that females are more influenced by subjective norms than are males in the usage of a new technology (Venkatesh and Morris, 2000). We also expect such differences to be present in individual consumption contexts.

P35: Consumer characteristics (e.g., frugality, impulsivity, income, and gender) moderate the effects of consumers' perceptions (e.g., about benefits and costs) on adoption and usage of a technological innovation.

## Discussion

### *Contributions and Research Agenda*

The proposed conceptual framework provides a "big picture," integrated view of individual-level determinants of consumers' adoption and usage of technological innovations. The extensive propositional inventory stemming from this framework suggests a number of specific linkages in the adoption-and-usage process that call for additional investigation. In the remainder of this section, we summarize several overall contributions of our work and highlight their implications for further research.

First, compared with previous research, our conceptual framework offers a deeper, more comprehensive, treatment of factors that affect consumers' adoption and usage of technology-based products and services. For example, we partition social benefits into two distinct components—one focusing on social *prestige* and the other on social *approval.* As another example, we not only distinguish between monetary costs and nonmonetary costs, but also further divide each of these two types of costs into distinct subcomponents. Such deeper conceptualization of the determinants could improve our ability to explain and predict the adoption and usage of technologically based offerings. The multidimensional conceptualization of the determinants of technology adoption and usage suggests a need and an opportunity for future researchers to design studies that lead to a finer-grained understanding of the adoption-and-usage process.

Second, our propositions suggest that the effects of some determinants may be more complex than is implied by previous research. For example, the perceived degree of newness of an innovation could have both positive and negative effects on its adoption and usage. Certain consumer characteristics could have direct as well as indirect effects on adoption and usage. Furthermore, some of these characteristics may moderate the effects of consumers' perceptions on their adoption and usage. The proposed framework serves as a blueprint for systematically studying such complexities and augmenting our knowledge base. Given the extensiveness of the framework, several future studies, each focusing on a small set of related propositions and linkages, may be necessary from the standpoint of both the feasibility and effectiveness of the research.

Third, the proposed framework introduces a number of antecedent constructs that have received little or no empirical-research attention. These include: (1) side effects, (2) expectations about the number of users, variety of use and rate of use, (3) general cognitions and feelings about technology, and (4) ownership of related products. The propositions pertaining to these constructs are especially in need of empirical examination to verify and, if necessary, revise them.

Fourth, the theoretical arguments underlying our framework suggest that although adoption and usage share a number of common antecedents, the effects of some of these antecedents on adoption are likely to differ from their effects on usage. It is worth investigating further and empirically verifying these differential effects because they imply that encouraging adoption and usage may require different marketing and communication strategies. Our work also suggests that the level of some determinants (e.g., perceived functional benefits) may change after adoption and initial usage. As such, future research employing longitudinal designs is needed to investigate changes over time in the determinants and their effects as consumers move from the pre-adoption stage to adoption to initial usage to continued usage. Such research has the potential to contribute significantly to extant knowledge about adoption and usage of technology-based products and services.

Fifth, our conceptual framework could serve as a starting point for incorporating external (as opposed to individual-level) determinants of adoption and usage. Such external determinants include marketing-mix elements, competition, and social network variables. Many of these antecedents are likely to exert their influence on the adoption and usage through consumers' perceptions and expectations—two of the three focal sets of antecedents examined in this chapter. Therefore, a potentially fruitful stream of research is to augment our proposed framework by examining, and incorporating when warranted, linkages from the external antecedents to the perceptual and expectations-based determinants already in the framework. After expanding the proposed framework in this manner, the possibility of any direct effects of the external antecedents on adoption and usage also needs to be investigated.

Lastly, our conceptual framework could be employed for studying the determinants of adoption speed, which relates to how fast an innovation is diffused in a social system (Rogers, 2003). Adoption speed can be defined as the multiplicative inverse of the duration between the introduction of the innovation in a market and the adoption by an individual in the market. On the basis of survival model theories (London, 1988), we expect that adoption speed is positively related to the probability of adoption discussed in this chapter. Therefore, we deduce that the determinants of adoption discussed here would also affect adoption speed in a similar way. Future research could therefore develop and test hypotheses about the determinants of adoption speed by referring to our propositional inventory and theoretical arguments.

### *Managerial Implications*

As implied by the discussion in the preceding section, the various linkages articulated in our propositional inventory are subject to empirical verification. Therefore, deriving *specific* managerial guidelines based on those propositions must await results from their empirical testing. However, our overall conceptual framework and its underlying theoretical arguments have several broad implications for makers and marketers of technology-based products and services. These implications pertain to product positioning, marketing communications, product/service design, and market segmentation.

The conceptual discussion and arguments supporting the perceptions component of the proposed framework suggest that consumers' perceptions about a technological innovation take on a "relative" perspective—that is, consumers compare the innovation with the product currently in use. Consequently, the product category against which a marketer explicitly positions an innovation could affect consumers' perceptions and hence their probability of adopting or using the innovation. For example, 3G cellular phones can be positioned as an enhanced version of 2G cellular phones. Alternatively, they can be positioned against personal digital assistants (PDAs)—as another type of handheld Internet device. Marketers need to give careful thought to the pros and cons of alternative ways of positioning an innovation before formulating a strategy for launching it.

Marketers of technological innovations often emphasize attributes such as functional benefits, hedonic benefits, and ease of use in their marketing communications. Although these attributes are important determinants of adoption and usage, our conceptual framework suggests that there are a number of other critical determinants as well—determinants that marketers might easily overlook. An example of such a determinant is the social prestige that an innovation could bestow upon adopters. Similarly, while emphasizing ease of *use* of an innovation, a marketer might overlook ease-of-*comprehension* and ease-of-*learning-to-use* issues, which may be just as critical in influencing consumers' adoption decisions. Consumers' perceptions about the ease of comprehension and ease of learning to use could be influenced by marketing communications efforts (e.g., advertising). In addition, a marketer could enhance these perceptions by improving consumers' perception about their self-efficacy. An effective way to improve their self-efficacy would be to provide them with training or support that enhances their knowledge related to the innovation concerned (Venkatesh, 2000; Venkatesh and Davis, 1996).

As another illustration of ignored aspects of an innovation, marketers typically tend to overemphasize the innovation's degree of newness without giving adequate consideration to the potential drawbacks of such a communication strategy. The proposed framework shows that the impact of degree of newness on adoption and usage is complex. Although communicating a high degree of newness can increase stimulation levels (and hence favorably impact adoption probability), beyond a certain point such communications might backfire. Moreover, consumers might associate higher degrees of newness with higher nonmonetary costs, thereby lowering the adoption probability. In short, our conceptual framework suggests that marketers should be careful in promoting their innovations as new products. Perhaps emphasizing that an innovation is moderately new could encourage adoption and usage, but promoting it as being very new may have negative effects on adoption and usage (Goldenberg et al., 2001). The complex effects of degree of newness also have implications for product design. Because consumers may arbitrarily focus on some features of an innovation in forming their first impressions about it (Ashcraft, 1989), features that are salient to them at the point of purchase may strongly influence their perceptions about the innovation's degree of newness. Therefore, companies need to pay careful attention to the design of an innovation's external features and the signals they are likely to send to consumers.

Our framework also suggests several direct, indirect, and moderating effects of consumer traits on adoption and usage of technological innovation. In personal selling situations, technology salespersons may be able to infer some of these traits from the behaviors and expressions of consumers. If so, the salespersons can adapt their selling strategy to improve their chances of making a sale. For example, emphasizing the functional benefits of a technological innovation might be appropriate for consumers who appear to be frugal, whereas emphasizing hedonic benefits might be appropriate in dealing with impulsive consumers. Similarly, if technology salespersons are able to infer consumers' general cognitions and feelings about technology, they can adapt their selling strategies accordingly. For example, if a consumer appears to be optimistic about technology in general, it would be beneficial for the salesperson to highlight the technology content of the new product. The aforementioned examples assume that the salespeople are capable of making accurate inferences about individual consumers and adapting their sales messages to fit those inferences. In reality, salespeople need to be trained to develop such capabilities. The key determinants in the proposed framework and their linkages to adoption and usage offer broad insights regarding the consumer traits and selling techniques to be emphasized in training programs for technology salespeople.

The characteristics of first-time users of a technological innovation may vary across different stages of an innovation's life cycle. Early adopters may tend to be rational, logical, and more optimistic about technology in general, whereas late adopters may rely more on their feelings in making judgments and tend to be more skeptical about technology in general (Dickerson and Gentry, 1983; Parasuraman and Colby, 2001). Owing to these variations in consumer characteristics across different stages, and given the relationships between these characteristics and adoption/usage, technology marketers need to vary their marketing strategies over time in order to capitalize on these changes.

Lastly, the consumer characteristics included in our framework offer some insights for market segmentation. In particular, the "related knowledge" characteristic may be an actionable segmentation criterion because of its potential relationships with certain observable characteristics, such as consumers' usage rates in related product categories and their educational levels. As our framework shows, related knowledge could affect comprehension of and hence perceptions about a technological innovation. By identifying which kind of knowledge facilitates comprehension and which kind of knowledge inhibits it, marketers of technological innovations could focus their marketing efforts on consumers with the *right* kind of knowledge. Other consumer characteristics, particularly income and occupation, may also serve as actionable segmentation criteria.

**Acknowledgments**

The authors are grateful to the audience of the Marketing & International Business Forum at the Nanyang Technological University for their constructive comments on the conceptual framework discussed in this chapter. The authors would also like to thank Naresh Malhotra (the Review of Marketing Research editor), Venkatesh Shankar, and David Gefen for their constructive comments on a previous version of this chapter.

## References


Agarwal, Ritu, and Elena Karahanna. (2000) "Time Flies When You're Having Fun: Cognitive Absorption and Beliefs About Information Technology Usage." *MIS Quarterly*, 24 (4), 665–694.

Agarwal, Ritu, and Jayesh Prasad. (1998) "A Conceptual and Operational Definition of Personal Innovativeness in the Domain of Information Technology." *Information Systems Research*, 9 (2), 204–215.

———. (1999) "Are Individual Differences Germane to the Acceptance of New Information Technologies?" *Decision Sciences*, 30 (2), 361–391.

Ajzen, Icek. (1988) *Attitudes*, *Personality and Behavior.* Chicago: Dorsey Press.

Ajzen, Icek, and Martin Fishbein. (1980) *Understanding Attitudes and Predicting Social Behavior.* Englewood Cliffs, NJ: Prentice-Hall.

Andersson, Per, and Kristina Heinonen. (2002) "Acceptance of Mobile Services: Insights from the Swedish Market for Mobile Telephony." In SSE/EFI Working Paper Series. Sweden: Business Administration, Stockholm School of Economics.

Ashcraft, Mark H. (1989) *Human Memory and Cognition*. New York: HarperCollins.

Bargh, John A., Mark Chen, and Lara Burrows. (1996) "Automaticity of Social Behavior: Direct Effects of Trait Construct and Stereotype Activation on Action." *Journal of Personality and Social Psychology*, 71 (2), 230–244.

Baumgartner, Hans, and Jan-Benedict E.M. Steenkamp. (1996) "Exploratory Consumer Buying Behavior: Conceptualization and Measurement." *International Journal of Research in Marketing*, 13 (2), 121–137.

Bearden, William O., Richard G. Netemeyer, and Jesse E. Teel. (1989) "Measurement of Consumer Susceptibility to Interpersonal Influence." *Journal of Consumer Research*, 15 (March), 473–481.

Bruner, Gordon C., and Anand Kumar. (2005) "Explaining Consumer Acceptance of Handheld Internet Devices." *Journal of Business Research*, 58 (May), 553–558.

Burroughs, Richard E., and Rajiv Sabherwal. (2001) "Determinants of Retail Electronic Purchasing: A Multi-Period Investigation." *INFOR*, 40 (1), 35–56.

Cervone, Daniel, and Walter Mischel. (2002) *Advances in Personality Science*. New York: Guilford Press.

Chau, Patrick Y.K., and Paul Jen-Hwa Hu. (2001) "Information Technology Acceptance by Individual Professionals: A Model Comparison Approach." *Decision Sciences*, 32 (4), 699–719.

Childers, Terry L., Christopher L. Carr, Joann Peck, and Stephen Carson. (2001) "Hedonic and Utilitarian Motivations for Online Retail Shopping Behavior." *Journal of Retailing*, 77 (4), 511–535.

Dabholkar, Pratibha. (1994) "Incorporating Choice into an Attitudinal Framework: Analyzing Models of Mental Comparison Processes." *Journal of Consumer Research*, 21 (1), 100–118.

Dabholkar, Pratibha, and Richard P. Bagozzi. (2002) "An Attitudinal Model of Technology-Based Self-Service: Moderating Effects of Consumer Traits and Situational Factors." *Journal of the Academy of Marketing Science*, 30 (3), 184–201.

Davis, Fred D. (1989) "Perceived Usefulness, Perceived Ease of Use and User Acceptance of Information Technology." *MIS Quarterly*, 13 (3), 319–340.

Davis, Fred D., Richard P. Bagozzi, and Paul R. Warshaw. (1989) "User Acceptance of Computer Technology: A Comparison of Two Theoretical Models." *Management Science*, 35 (8), 982–1003.

Dickerson, Mary Dee, and James W. Gentry (1983) "Characteristics of Adopters and Non-Adopters of Home Computers." *Journal of Consumer Research*, 10 (2), 225–235.

Fisher, Robert J., and Linda L. Price (1992) "An Investigation into the Social Context of Early Adoption Behavior." *Journal of Consumer Research*, 19 (3), 477–486.

Fiske, S.T. (1982) "Schema-triggered Affect: Applications to Social Perception." In *Cognitive Social Psychology*, ed. A.H. Hastorf and A.H. Isen, pp. 55–78. New York: Elsevier.

Gatignon, Hubert, and Thomas S. Robertson. (1985) "A Propositional Inventory for New Diffusion Research." *Journal of Consumer Research*, 11 (4), 849–867.

Gefen, David, and Detmar W. Straub. (1997) "Gender Differences in Perception and Adoption of E-Mail: An Extension to the Technology Acceptance Model." *MIS Quarterly*, 21 (4), 389–400.

Gefen, David, Elena Karahanna, and Detmar W. Straub. (2003a) "Inexperience and Experience with Online Stores: The Importance of TAM and Trust." *IEEE Transactions on Engineering Management*, 50 (3), 307–321.

———. (2003b) "Trust and TAM in Online Shopping: An Integrated Model." *MIS Quarterly*, 27 (1), 51–90.

Goldenberg, Jacob, Donald R Lehmann, and David Mazursky. (2001) "The Idea Itself and the Circumstances of Its Emergence as Predictors of New Product Success." *Management Science*, 47(1), 69–84.

Hirschman, Elizabeth C. (1980) "Innovativeness, Novelty Seeking, and Consumer Creativity." *Journal of Consumer Research*, 7 (December), 283–295.

Karahanna, Elena, Detmar W. Straub, and Norman L. Chervany. (1999) "Information Technology Adoption Across Time: Cross-Sectional Comparison of Pre-Adoption and Post-Adoption Beliefs." *MIS Quarterly*, 23 (2), 183–213.

Lastovicka, John L., Lance A. Bettencourt, Renee Shaw Hughner, and Ronald J. Kuntze. (1999) "Lifestyle of the Tight and Frugal: Theory and Measurement." *Journal of Consumer Research*, 26 (June), 85–98.

Leake, Jonathan. (2004) "Mobile Phones Can Cut a Man's Fertility by a Third." *The Sunday Times*, No. 9383 (27 June), 1.1. Brussels, Belgium.

London, Dick. (1988) *Survival Models and Their Estimation*. 2d ed. Winsted and Avon, CT: ACTEX Publications.

Mick, David Glenn, and Susan Fournier. (1998) "Paradoxes of Technology: Consumer Cognizance, Emotions, and Coping Strategies." *Journal of Consumer Research*, 25 (September), 123–147.

Moore, G.C., and I. Benbasat. (1991) "Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation." *Information Systems Research*, 2 (3), 192–222.

Moreau, C. Page, Donald R. Lehmann, and Arthur B. Markman. (2001) "Entrenched Knowledge Structures and Consumer Response to New Products." *Journal of Marketing Research*, 38 (1), 14–29.

Morris, Michael G., and Viswanath Venkatesh. (2000) "Age Differences in Technology Adoption Decisions: Implications for a Changing Work Force." *Personnel Psychology*, 53 (2), 375–403.

Parasuraman, A. (2000) "Technology Readiness Index (TRI): A Multiple-Item Scale to Measure Readiness to Embrace New Technologies." *Journal of Service Research*, 2 (4), 307–320.

Parasuraman, A., and Charles L. Colby. (2001) *Techno-Ready Marketing: How and Why Your Customers Adopt Technology*. New York: The Free Press.

Petty, Richard, and John T. Cacioppo. (1986) "The Elaboration Likelihood Model of Persuasion." *Advances in Experimental Social Psychology*, 19, 123–205

Plouffe, Christopher R., John S. Hulland, and John Vandenbosch. (2001) "Richness Versus Parsimony in Modeling Technology Adoption Decisions-Understanding Merchant Adoption of a Smart Card-Based Payment System." *Information Systems Research*, 12 (2), 208–222.

Raju, P.S. (1980) "Optimum Stimulation Level: Its Relationship to Personality, Demographics, and Exploratory Behavior." *Journal of Consumer Research*, 7 (December), 272–282.

Rogers, Everett. (2003) *Diffusion of Innovations*. 5th ed. New York: The Free Press.

Rook, Dennis W. (1987) "The Buying Impulse." *Journal of Consumer Research*, 14 (September), 189–199.

Rook, Dennis W., and Robert J. Fisher. (1995) "Normative Influences on Impulsive Buying Behavior." *Journal of Consumer Research*, 22 (December), 305–313.

Russell, Gary, David Bell, A. Bodapati, C. Brown, Jeongwen Chiang, G. Gaeth, P. Manchanda, and S. Gupta. (1997), "Perspective on Multiple-Category Choice." *Marketing Letters*, 8 (3), 297–306.

Shankar, Venkatesh, and Barry L. Bayus. (2002) "Network Effects and Competition: An Empirical Analysis of the Home Video Game Industry." *Strategic Management Journal*, 24 (4), 375–384.

Shih, Chuan-Fong, and Alladi Venkatesh. (2004) "Beyond Adoption: Development and Application of a Use-Diffusion Model." *Journal of Marketing*, 68 (January), 59–72.

Shocker, Allan D., Barry L. Bayus, and Namwoon Kim. (2004) "Product Complements and Substitutes in the Real World: The Relevance of 'Other Products.'" *Journal of Marketing*, 68, 28–40.

Steenkamp, Jan-Benedict E.M., and Hans Baumgartner. (1995) "Development and Cross-Cultural Validation of a Short Form of CSI as a Measure of Optimum Stimulation Level." *International Journal of Research in Marketing*, 12, 97–104.

Sujan, Mita. (1985) "Consumer Knowledge: Effects of Evaluation Strategies Mediating Consumer Judgments." *Journal of Consumer Research*, 12 (June), 31–46.

Taylor, Shirley, and Peter A. Todd. (1995) "Understanding Information Technology Usage: A Test of Competing Models." *Information Systems Research*, 6 (2), 144–176.

Venkatesh, Viswanath. (2000) "Determinants of Perceived Ease of Use: Integrating Control, Intrinsic Motivation, and Emotion into the Technology Acceptance Model." *Information Systems Research*, 11 (4), 342–365.

Venkatesh, Viswanath and Susan A. Brown. (2001) "A Longitudinal Investigation of Personal Computers in Homes: Adoption Determinants and Emerging Challenges." *MIS Quarterly*, 25 (1), 71–102.

Venkatesh, Viswanath, and Fred D. Davis. (1996) "A Model of the Antecedents of Perceived Ease of Use: Development and Test." *Decision Sciences*, 27 (3), 451–481.

———. (2000) "A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies." *Management Science*, 46 (2), 186–204.

Venkatesh, Viswanath, and Michael G. Morris. (2000) "Why Don't Men Ever Stop to Ask for Directions? Gender, Social Influence and Their Role in Technology Acceptance and Usage Behavior." *MIS Quarterly*, 24 (1), 115–139.

Venkatesh, Viswanath, Michael G. Morris, Gordon B. Davis, and Fred D. Davis. (2003) "User Acceptance of Information Technology: Toward a Unified View." *MIS Quarterly*, 27 (3), 425–478.

Zeithaml, Valarie A., and Mary C. Gilly. (1987) "Characteristics Affecting the Acceptance of Retailing Technologies: A Comparison of Elderly and Nonelderly Consumers." *Journal of Retailing*, 63 (1), 49–68.

Zhao, Shenghui, Robert J. Meyer, and Jin K. Han. (2003) "The Rationality of Consumer Decisions to Adopt and Use New Technologies: Why Are We Lured by Product Features We Never Use?" Singapore: The Wharton-Singapore Management University Research Center.

CHAPTER 6

# THE METRICS IMPERATIVE

## Making Marketing Matter

DONALD R. LEHMANN

**Abstract**

*Recently, there has been increased pressure for marketing to justify its budgets and activities. This chapter briefly reviews the reasons behind the pressure. It then develops a metrics value chain to capture the various levels of measurement employed and discusses evidence for the various links in the chain. Problems in establishing the links are then discussed, and suggestions for future work are offered.*

**The Metrics Imperative: Making Marketing Matter**

Many in marketing have been concerned about the financial consequences of marketing for a long time. The current push for metrics that demonstrate the productivity of marketing (e.g., Kirplani and Shapiro, 1973), however, has largely come from outside the field. Specifically, CEOs and CFOs, spurred by global competition, recession, and stock market pressure to deliver "the numbers," have increasingly questioned marketing budgets and shown an increased willingness to cut them. The response by many members of the marketing profession has been less than enthusiastic, falling back on arguments that are essentially nihilistic (i.e., it can't be done, or at least done precisely, so why bother) or, in the case of many at least in academia, deciding it isn't their problem. Still, several scholars have advocated better metrics. Perhaps the seminal piece is Srivastava, Shervani, and Fahey (1998), which connects marketing assets to stockholder value. In addition, the Marketing Science Institute (MSI) has had metrics and marketing productivity as a top research priority from 1997 to 2006 based on surveys of its member companies. The large and increasing fraction of shareholder value (market capitalization) attributable to intangible assets such as customers and brands has added further impetus to a drive toward making marketing expenditures at least more accountable (Doyle, 2000a; Rust et al., 2004).

Of course, not all firms are concerned with maximizing stock value. Privately held firms may be legitimately more concerned with maintaining a steady stream of income or preparing for an IPO. Other firms' goals include short-term cash flow or obtaining "hard" currency. Moreover, the large set of nonprofit institutions have other goals, such as to expand the number who receive treatment for a particular condition and their adherence to treatment, to maintain and expand membership and their impact on society, or even the fuzzy but lofty goal of creating and disseminating knowledge. This chapter, however, focuses on for-profit firms that are either publicly held or whose objectives can be defined in terms of product-market results.

Firms and individual researchers are often content with results that apply to a very narrow range of situations (i.e., a single company in a single product category). Developing a situation-value chain is indeed a worthwhile activity. However, it is also time consuming. Further, in the Bayesian statistical sense, the results are inefficient since they ignore related information (e.g., paper towels vs. paper napkins). Finally, because the purpose of this chapter is general, it focuses on studies that cover multiple products/services and the development of a general metrics value chain.

## Metrics Hierarchy Versus Metric Dashboard

The current practice in many organizations is to develop a "dashboard" with multiple measures (Kaplan and Norton, 1996; Ambler and Kokkinaki, 1988). These measures all have value to someone in or outside the organization. Furthermore, by using a system such as colors (green is good, red is bad), it is possible to get a general impression of how things are going. Unfortunately, dashboards have three major shortcomings. First, even with clever presentation they can be a bit overwhelming. Second, since changes in indicators such as customer satisfaction are critical, they need to contain not just level but also change measures, making them relatively complex. Third, and most critical, they often do not identify what drives what, much less indicate the impact of one variable on the others. For that reason many practitioners as well as academics are interested in capturing the links in a "value chain." For example, Hewlitt-Packard has developed a model linking customer experience and brand development to product market and financial market performance. For that reason we organize this discussion in terms of a metrics hierarchy/causal chain.

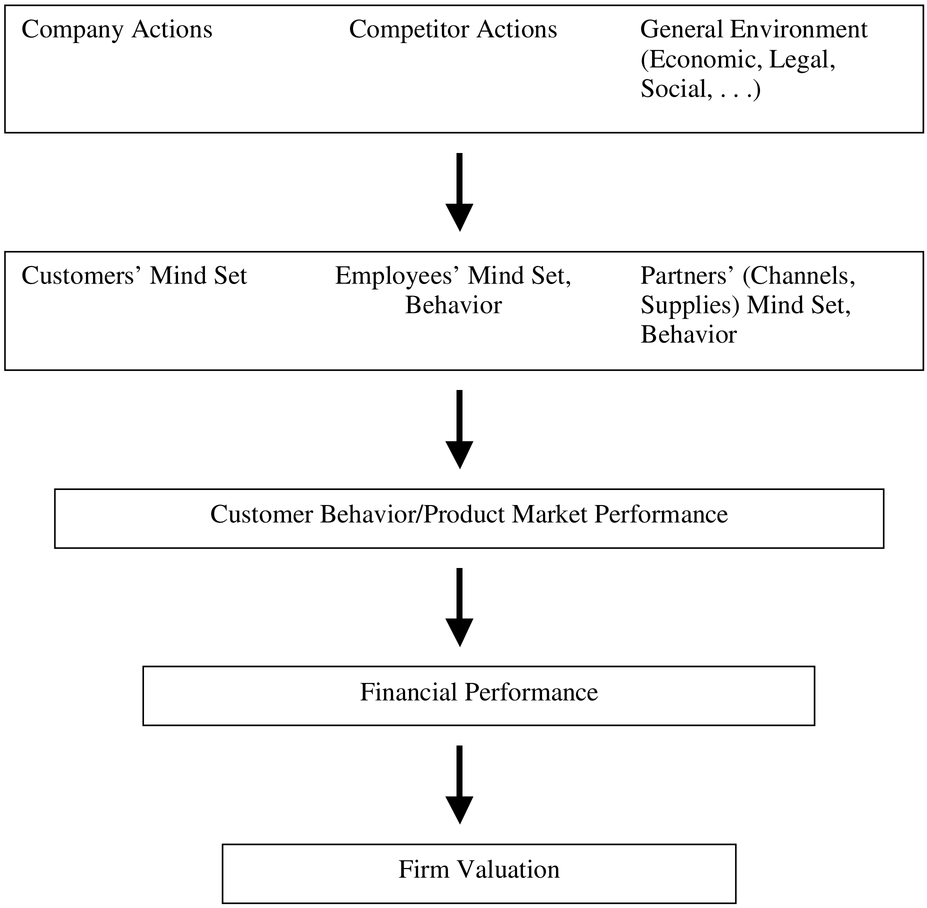
Numerous measures of marketing effectiveness exist. A number of authors have developed models of how these various metrics link together. These include the Service Profit Chain (Heskett et al., 1994; Kamakura et al., 2002), the Brand Value Chain (Keller and Lehmann, 2003), and the Chain of Marketing Productivity (Rust, Lemon, and Zeithaml, 2004) as well as the models presented by Srivastava, Shrevani, and Fahey (1998) and Lehmann (2004). Based on these, Figure 6.1 presents a framework for linking company actions with product-market and financial performance.

Behind the push for marketing metrics is the need to demonstrate the productivity of marketing actions and spending. For a publicly held company, the ultimate goal is the stock price. Of course, this ignores numerous other stakeholders including employees, the community where business is conducted, and society as a whole. How much these should be considered is the matter of some debate. Since adequately dealing with these other parties is a major task in its own right, however, here we focus on stock price as the ultimate goal.

Even if stock price is the ultimate goal, however, it is not always operationally very helpful either as a performance indicator or diagnostically. Few actions (e.g., a single ad, promotion, or line extension) have a pronounced effect on stock price. While a general strategy or policy (e.g., an emphasis on new products) may impact stock price, at least across companies, the impact of most individual marketing decisions is limited. For that reason, intermediate goals are utilized. The problem with doing this is twofold. First, the intermediate goals used have often been far removed from stock price (e.g., awareness). Moreover, these criteria have differed across marketing decisions (e.g., awareness and attitude to the ad and the product for advertising , the immediate increase in sales from a promotion) making it difficult to compare, say, advertising and promotion effectiveness. Thus, at a minimum there is a need to calibrate effectiveness across measures.

The phenomenon of marketing dashboards, an outgrowth of "Balanced Scorecard" think-

Figure 6.1 **Metrics Value Chain**




ing (Kaplan and Norton, 1996), demonstrates the issue. While these devices produce many important diagnostic indicators, they often fail to produce a clear sense of what impacts financial performance. As a consequence, what is needed is the next phase of dashboards where links among the measures are both highlighted and estimated. The goal, then, is to establish the strength of the links so that even when not all measures are available, one can estimate the impact of marketing actions. A value chain similar to Figure 6.1 provides the basis for such a model.

The top level of the chain consists of actions of the company, competitors, and industry and environment in general. Of particular interest are company actions, the decision variables available to a firm (e.g., R and D and advertising spending, customer targeting).

The initial impact of these variables is on the mind-set of customers as well as employees, partners, etc. as well as on others in the top level (e.g., the impact of company actions on competitors as indicated by reaction functions). For example, the main customer concern of Procter and Gambel and Colgate may be the reaction of Wal-Mart. In any event, the impact on customers (current and potential) is critical. This leads to the use of measures of awareness (knowledge), associations (both product attribute and image based), attitude, and attachment/loyalty.

The third stage involves customer behavior (vs. mind-set) in the product market. At the aggregate level this includes sales, share, average price paid, and share of wallet, as well as response sensitivities such as own and cross price elasticities. A large literature exists which examines the product-market impact of mix elements such as advertising (Allenby and Hanssens, 2004)

The consequence of product market results is financial performance. Measures such as net profit, return on investment (ROI), and return on assets (ROA) fall in this category as well as EVA (economic value added—basically net profit adjusted for the opportunity cost of capital tied up in the business).

The final category is the ultimate objective, stock price or variations of it such as MVA (market value added—change in market capitalization), or Tobin's q (basically stock price divided by book value with some adjustments). Of course, stock price (firm valuation) is not always the ultimate goal. For non-profits, product market behavior is often the goal/and financial performance of the constraint (e.g., eating less fat, developing cures for disease). Similarly, privately held firms may focus on generating streams of earnings or employment for family members.

Part of the reason for the absence of a single set of measures is that different people focus on different measures. The differences are to a large extent a function of where they are in the organization. To oversimplify:

| **Level of the Metric** | **Main Constituency** |
|---|---|
| Customer Mind-Set | Marketing Specialists (Advertising Promotion, Product Development) |
| Product-Market Performance | Product Managers, Chief Marketing Officers (CMOs) |
| Financial Performance | CMOs, CFOs |
| Firm Valuation | CFOs, CEOs |

For example, someone trying to fine-tune a promotion decision for one of many products rightly spends little time worrying about stock price. Similarly, someone charged with business unit or corporate results has little time to focus on diagnostic measures of consumer thinking. Rather, they concentrate on profit and ROI. This leads, unfortunately, to the business equivalent of the Tower of Babel, with different parts of the organization speaking different languages.

## Key Metrics

The term *metrics* is far from precise. Under each general category (e.g., customer mind-set), several metrics have been proposed and utilized. Since all capture different facets of a basic construct, the use of different metrics can alter results and interpretations. Appendix 6.1 shows a partial list of metrics that either have been or could be used. Here we highlight three that are especially critical in assessing marketing effectiveness.

### *Satisfaction*

The satisfaction concept has been a central one in marketing for a long time (e.g., Howard and Sheth, 1969; Oliver, 1997). Basically, it captures the reaction to a product or service after use (see Zeitamhl and Parsuaraman, 2004). Most current measures are based on the "gap" model

(Parsuraman, Zeithaml, and Berry, 1988, 1994). Effectively, this means comparing observed with actual performance. Evidence suggests that both actual and expected performance also directly impact satisfaction (although in a regression model, only two of the three terms can be included because of collinearity).

At least two key issues arise related to measuring satisfaction. First, is it "episodic"—that is, related to a single situation, or cumulative, with the latter being both more stable and more closely related to other concepts such as brand equity, quality, and attitude? Second, what are the relevant standards of comparisons; for example, ideal, should, or will expectations (Boulding, Kalra, Staelin, and Zeithaml, 1993) or strategically managed as-if expectations (Kopalle and Lehmann, 2001)? Third, how do comparisons with these standards combine with other considerations such as payoffs (equity) and procedural justice to form overall satisfaction? Fourth, do we measure satisfaction for all users, nonusers, heavy users, and so on, and once measured, do we report it for subgroups or overall or for some weighted average across groups? Most important, is satisfaction an appropriate measure of performance?

A tremendous amount of literature has focused on satisfaction as a de facto criterion measure—for example, the work on salesforce satisfaction and satisfaction with channel partners (Geyskens, Steinkamp, and Kumar, 1998). Still, evidence suggests maximizing satisfaction does not necessarily maximize produce-market performance (e.g., sales, share, profits). As a consequence, there may be an optimal level of satisfaction. This makes interpretation of satisfaction score less straightforwardly since more is not necessarily better.

### *CRM and CLV*

Customer relationship management is one area of marketing where metrics are both widely available and utilized. This work builds heavily on the practices of direct marketing, which traditionally kept track of customers on an individual basis and assessed customers in terms of RFM: Recency (how recently customers bought something), Frequency (how often they bought), and Amount (how much they bought).

The basic metric in this area is Customer Lifetime Value (CLV), which assesses a customer's long-run product market behavior. The principal approach is to treat each customer as an asset that has a probability of ending each period (i.e., defection) and generates a stream of (net of variable cost) earnings, which is then discounted back to the present (Berger and Nasr, 1998; Blattberg and Deighton, 1996). Cost considerations include both acquisition and retention costs.

Like all metrics, this one raises some issues. First, when a customer defects, while it may not be forever, the simple CLV formula does not allow for the customer to return. Hogan, Lemon, and Libai (2003) capture some of this by distinguishing between whether a customer defects to a competitor (from which they may return) or disadopts the product category. Even more fundamental, it is often impossible to say with certainty if a customer has defected for good or merely slowed purchases. Although statistical modeling can give some insight here (Schmittlein, Morrison, and Colombo, 1987), most CLV formulations are deterministic rather than stochastic. Moreover, most CLV formulas capture direct value through purchases. This leaves out both word-of-mouth and network effects, which can be substantial. Also importantly, the data that goes into CLV calculations and the resulting calculated value are myopic. More specifically, in general, databases have information on transactions only with one firm. As a result, they have no sense of either customer potential or their share of market requirements or wallet. Perhaps most critical, CLV is predicted based on forecasts of customer margin, retention rate, and retention cost. Like most forecasts, this one is based on assumptions and has a notable error associated with it—

something that should be explicitly acknowledged (e.g., with a plus or minus range) or explored by presenting alternative scenarios in a sensitivity analysis but rarely is.

One implication that results from examining the algebra of CLV as well as other work (Reichheld and Teal, 1996) is that retention is key. Indeed, retention is a critical metric, possessing more marginal impact on CLV than either acquisition cost or the discount rate. Still, maximizing it probably means “leaving money on the table.” Not only does maximizing retention ignore the fact that some customers are not profitable, but it, like satisfaction, is easier to maximize by focusing on a small segment of customers.

The point here is not that CLV is a bad measure. Indeed, it has proved quite useful (Reinartz and Kumar, 2004) and is related to overall firm value (Gupta, Lehmann, and Stuart, 2004). Rather, the point is that it, like all metrics, has advantages and disadvantages and provides, to use another metaphor, both highlights and shadows.

### *Brands and Brand Equity*

Brands, which have been studied extensively in marketing (Keller and Lehmann, 2005), represent a significant fraction of the intangible, and hence total, value of many firms. This has led to attempts to include brand value on the balance sheets of firms in the UK (Kallapur and Kwan, 2004). A key issue, therefore, is how to estimate brand value.

Measuring brand value (equity) raises two critical questions. The first is conceptual: does it refer to the value of the brand to the customer or the value of the brand to the firm (aggregated across customers). Typically, those in the marketing function take the customer-centric view while those higher in the organization or outside marketing take the firm view (Ambler and Barwise, 1998).

The second question is whether it can be captured by a single measure. Obviously, for diagnostic purposes, multiple measures are helpful. For example, the sales and price premiums for a brand are components of a variance analysis of the revenue premium and capture different aspects of brand equity at the product-market level. Similarly awareness, associations, and satisfaction capture different aspects of what consumers think of products. Furthermore, the various components are not necessarily highly correlated, meaning they may not pass the standard tests for the undimensionability of a construct. As a consequence, many in marketing argue that no single measure adequately captures the construct. On the other hand, many outside marketing (and some inside it as well) find the discussion of nuances convoluted and not very helpful. They want a single measure because, for example, they have to decide how much to pay to acquire a brand.

As a consequence, in practice brand metrics vary widely (Table 6.1). Some are conceptually incomplete but still informative. For example, at the firm level, share contains the effect of other elements of the mix (e.g., price) and competition which need to be removed before brand equity can be assessed, and the price premium is a result of a strategic decision about whether to take the benefits of equity in volume versus margin. In the metrics value chain, nuanced (multiple) customer-level measures occur at the beginning of the chain, whereas firm-level financial market measurers represent the end of the chain. In other words, the various measures are causally, if imprecisely, related.

It is also useful to recognize the relation between brand equity and customer equity. Essentially, the value of a customer is the sum across all products that the customer purchases of the “normal” margin which any product in its category would generate (which in pure competition approaches zero) and the extra margin attributable to a brand (Table 6.2). Thus, total customers lifetime value generally exceeds product-market level brand equity.

Table 6.1

**Perspectives on Brand Equity**

| Customer level (value to customer) | Firm level (value to firm) |
|---|---|
| Mind set | Product market: |
| Awareness | Stocking level (ACV) |
| Associations | Price premium |
| Attitude | Sales premium |
| Attachment (loyalty) | Revenue premium |
| | Brand constant in a logit model |
| Behavior | |
| Purchases revenue | Financial Market: |
| Share off wallet | Tobin's Q |
| Activity | MVA |
| | Value in mergers and acquisitions |
| Financial | |
| CLV | |

Table 6.2

**Sources of Business by Brand and Customer**

| | Brand A | | Brand B | | |
|---|---|---|---|---|---|
| | Product 1 | Product 2 | Product 3 | Product 4 | Total |
| Customer | a, b | a, b | a, b | a, b | a & b values |
| 1 | | | | | |
| 2 | | | | | |
| . . . | | | | | |
| . . . | | | | | |
| . . . | | | | | |
| n | | | | | |
| Total a | PR A1 | PR A2 | PR B3 | PR A4 | |
| Total b | BE A1 | BE A2 | BE B3 | BE B4 | Value of Customer |

a = Attribute-driven revenue (economic and functional benefits)
b = Brand-driven revenue (extra due to brand)
PR = Product revenue
BE = Brand equity

## Links in the Chain

### *Marketing Actions to Customer Mind-Set*

Because of the need for customer insight at the firm level (e.g., to assess the impact of advertising copy and possible new products prior to implementation or introduction), companies frequently resort to measuring customer perceptions, attitudes, and intentions. The emergence of positions with titles like Customer Insights Manager highlights this emphasis. This is also the focus of much of the academic work in information processing and consumer behavior and represents a large and disparate literature which is the subject of numerous books, articles, and courses. For the purposes of this chapter we will take this link as established, though not well calibrated in a general, meta-analytic sense (e.g., how large is the increase on an attitude scale when an additional ad exposure is encountered?).

One interesting question is the link among company claims, customer expectations, actual quality, and satisfaction. In a series of studies, Kopalle and Lehmann (1995, 2001) demonstrate that the promise made (e.g., in ads) affect both satisfaction and subsequent behavior.

### *Marketing Actions to Product-Market Results*

This link has been the focus of much of the marketing science literature. One approach here is analytical. Considerable economic modeling addresses these issues, and, when a closed-form solution emerges, the link is explicit. Such solutions, however, have not found wide acceptance in practice unless calibrated on company-specific data, partly because the assumptions are typically quite restrictive and hence not realistic (e.g., two competitors, two segments of customers, costs equal or zero, two-period horizon). In general, realistic modeling and mathematical tractability are inconsistent goals. More general models can be addressed with numerical methods, including the recent developments in agent-based simulation (Goldenberg, Labai, and Muller, 2004; Lusch and Tay, 2004). While much of the field seems to consider numerical methods intellectually inferior, this approach has much to commend it. Still, for the sake of credibility, empirical results are generally required.

Empirical work on the impact of advertising is widespread (Allenby and Hanssens, 2004; Vakratsas and Ambler, 1999). In terms of generating generalizations, various meta-analyses exist, including Eastlack and Rao (1986), Assmus, Farley, and Lehmann (1984), Batra, Lehmann, Burke and Pae (1995), Lodish et al. (1995), Riskey (1997), and Sethuraman and Tellis (1991). The basic findings are very consistent. Spending more money on a mature product with nothing new to say has little short-run impact in terms of sales (elasticity 0–0.03), whereas ad spending on a new product or new use of an old product is noticeably more effective (elasticity around 0.3). This has direct implications for both budget setting and evaluation (i.e., a proposed 50% increase in ad spending for a mature product alone is unlikely to produce a 10% increase in unit sales) and allocation (i.e., generally allocating more to new products with high sales growth than old products with high sales levels is preferable). Advertising may have an indirect impact on sales, however, through its effect on price sensitivity (Kaul and Wittink, 1995). It also has an impact on volatility (Merino, Srinivasan, and Srivastava, 2003)

The promotion area has been at least as widely studied (Neslin, 2002). Here the evidence generally suggests that promotions have a positive short-run and negative long-run impact with the total effect positive, at least in the absence of (likely) competitive reactions (e.g., Mela, Gupta, and Lehmann, 1997; Nijs et al., 2001). This is consistent with the noticeable drop in share that P and G suffered when it cut promotions and competition failed to follow (Ailawadi, Lehmann, and Neslin, 2001). In addition, several researchers have investigated the impact of promotions in the pharmaceutical industry (e.g., Narayanan, Desiraju, and Chintagunta, 2004).

In terms of channels and product, there is less available evidence. Much of the channels literature has focused on information use and relationship quality (trust, satisfaction) and linked these to self-rated performance scales (e.g., Geyskens, Steenkamp and Kumar, 1998); Moorman, Zaltman, and Desphande, 1992; Moorman, Desphande and Zaltman, 1993). There is evidence that long term relationships improve performance in a B to B setting (Kumar, 1999).

Similarly, there is a vast literature on new products (Hauser, Tellis, and Griffin, 2004), much of it focused on development. Considerable effort has been directed toward addressing the pattern of product diffusion, much of it using the Bass (1969) model (Gatignon, Eliashberg, and Robertson, 1989; Golder and Tellis, 1997; Sultan, Farley, and Lehmann, 1990). Bass models the probability of adoption of a new product in the next period given that a person has not yet adopted as $p + q$ (Past Adoption/Market Potential). Here $p$ represents the tendency to adopt on one's own (innovate) based on company-supplied and generally available information, and $q$ represents the tendency to adopt because others have adopted (imitate due to word of mouth, etc.). The results suggest that (a) Bass model parameters are 0–0.04 for $p$ (meaning innovation is fairly rare) and around .3 for $q$ for consumer durables, (b) there is a lag between introduction and takeoff of several years, and (c) patterns vary by country (Gatignon, Eliashberg, and Robertson, 1989; Tellis, Stremersch, and Yin, 2003).

Taken together, the results are interesting but provide relatively few empirical generalizations and quantitatively estimated contingencies. As a consequence, it is difficult to convince managers that a result such as a 2% increase in sales is likely without a "one-off" special study. Similarly, it is difficult to produce realistic budget and P and L statements a priori. As a consequence, management's attention is diverted from strategic issues to tactical ones such as promotion (Bucklin, Lehmann, and Little, 1998) where measurement capabilities are better.

### *Marketing Capabilities and Strategy to Product-Market Results*

One area already discussed in which substantial work has been done is the impact of brand equity. Generally, the results show that brand equity reduces sensitivity to price increases and makes advertising more effective as well as directly creating a "revenue premium" for the firm (Ailawadi, Lehmann, and Neslin, 2003; Erdem and Sun, 2002). One consequence of this is the difference in price elasticity between national and store brands (Sethuraman, 1995).

The impact of new product entry order on sales has also been extensively studied. Most studies find an advantage to early entry (e.g., Kalyanaram, Robinson, and Urban, 1995; Szymanski, Troy, and Bharadwaj, 1995), although the advantage may be overstated unless one accounts for market failures and exists. Success depends on the ability of the firm to capture the evolving mass market (Golder and Tellis, 1993). Put differently, being first on average helps but is far from a panacea. Rather the strategic response to a new technology has an important impact on performance (Lee and Grewal, 2003).

Numerous studies have focused on the concept of market orientation (Despande, Farley, and Webster, 1993; Kohli and Jaworski, 1990; Narver and Slater, 1990). It has generally been positively linked to market performance (Greenley, 1995; Harris, 2001; Pelham, 1999; Pelham and Wilson, 1996; Slater and Narver, 1994), and innovativeness (Despande and Webster, 1989), although its impact depends on market conditions (Slater and Narver, 1994). More specifically, Dutta, Narasimhan, and Rajiv (1999) demonstrated the importance of marketing capability in high-tech markets. Interestingly, the impact may be more on performance variance than on its level (Capon, Farley, and Hoenig, 1990). That is capabilities such as market orientation (or measures such as satisfaction and customer retention) may have greater impact on the variance than the mean results. If this is the case, then by reducing earnings variability, marketing can enhance stock price.

An important additional aspect relates to employee orientation. Employee satisfaction has been shown, unsurprisingly, to relate to customer loyalty and profitability (Loveman, 1998),

### *Customer Mind-Set to Product Market*

One clearly established result is that satisfaction links to product-market results (Zeithaml and Parasuraman, 2004). Satisfaction improves repeat purchase rates and generates favorable word-of-mouth (Rust and Zahorik, 1993). The amount of the increase (for example, in terms of elasticity), however, is not widely reported, and here again empirical generalizations are lacking. Similarly, as in many links, the issue of simultaneity arises. To what extent does satisfaction generate positive word of mouth versus vice-versa? How much of satisfaction is dissonance reduction?

### *Customer Mind-Set to Financial Performance*

As suggested earlier, satisfaction is probably the key mind-set metric in terms of predicting retention and hence CLV and firm value. Importantly, there is evidence that satisfaction relates to firm ROA. Anderson, Fornell, and Lehmann (1994) developed a specific estimate of the impact of a point of satisfaction on ROA. Basically, they found that a 1-point increase in satisfaction (on a 100-point scale) each year over five years generated over a 10% increase in ROA for Swedish firms. Anderson, Fornell, and Rust (1997) compare the impact of satisfaction for goods and services, while Hallowell (1996) relates satisfaction directly to profitability. Moreover, Ittner and Larcker (1998), Bernhardt, Donthu, and Kennet (2000), and Anderson, Fornell, and Mazvancheryl (2004) demonstrate the link between customer satisfaction at the aggregate level and several measures of shareholder value. One key issue, then, concerns not whether satisfaction relates to financial performance but rather the strength and form (which is logically nonlinear) of the relation. Of course, to be useful, we also need to know the impact of marketing actions on satisfaction.

Relatively little is known about the links of most other mind-set measures to either product-market behavior or financial performance. For example, considerable effort has been expended analyzing brand associations, including image (e.g., modern) and personality (e.g., sincere). How this translates into sales, profit, etc. is unclear either for specific cases or classes of products in general. Given the current refusal of CEOs to accept "justification by faith" arguments, this poses a relevance problem for marketers working on these fuzzy but potentially critical variables.

### *Marketing Actions to Financial Performance*

One interesting example of this link is Joshi and Hanssens (2004), who link advertising spending to stock performance, echoing the work of Hirschey (1982), Cheng and Chen (1997), Chauvin and Hirschey (1993), and Graham and Frankenberger (2000). Jose, Nichols, and Stevens (1986) assessed the impact of promotion. Even the act of changing an ad slogan can impact the market value of a firm (Mathur and Mathur, 1995). In addition, Ailawadi, Borin, and Farris (1995) demonstrated a link between marketing actions, economic value added (EVA), and market value added (MVA). Other studies have addressed the impact of customer service changes (Nayyar, 1995) and event sponsorship (Miyazaki and Morgan, 2001) on stock market value as well as service quality in general (Zeithaml, 2000). Erickson and Jacobson (1992) and Graham and Frankenberger (2000) assess the impact of recession on the effectiveness of marketing activities. Recently, Pauwels, Silva-Risso, Srinivasan, and Hanssens (2004) found that new product introductions, especially in a new market, increase long-term financial performance but promotions do not.

In the new product area, both Chaney, Devinney, and Winer (1991) and Lane and Jacobson (1995) demonstrate a positive impact of new product announcements on stock price. In fact, the impact of new product announcements and introductions has been studied fairly extensively both inside marketing (Koku, Jagpal, and Viswanath, 1997) and outside (Cooper, 1984; Eddy and Saunders, 1980; Pardue, Higgins and Biggart, 2000).

More broadly, product quality has an obvious link to financial value as the negative impact of product recalls demonstrates (Jarrell and Peltzman, 1985). Similarly, patient perceptions of quality impact hospital financial performance (Nelson et al., 1992). Rust, Zahorik, and Keiningham (1995) assessed the financial impact of quality on market value, Hendricks and Singhal (1996) related quality awards to market value, and Itner and Larker (1996) studied quality initiatives, while Jarrell and Peltzman (1985) show the impact of product recalls. Rust, Moorman, and Dickson (2002) then separated the impact of quality into cost reduction and revenue expansion. More generally, one study suggested that ethical behavior may improve financial performance (Cloninger et al., 2000). This raises the question of when "doing well by doing good" is true and when doing good requires an objective function broader than profits or stock price.

### *Marketing Assets to Financial Performance*

Linking strategy to performance (Day and Fahey, 1988; Doyle, 2000b) has a long history punctuated by the PIMS (Profit Imact of Marketing Strategy) project, which originated at General Electric (Buzzell and Gale, 1987). In that tradition, Doukas and Switzer (1992) relate market concentration and stock market valuation, Rao, Agarwal, and Dahlhoff (2004) found that firms that employed an umbrella (corporate) brand were valued by the stockmarket more highly than firms with multiple brands, perhaps to compensate for the greater risk of such a nondiversified strategy. Mizik and Jacobson (2003) studied relative spending on R&D (long-run "value creating") versus Advertising and Promotion (short-run" "value appropriating"). They found that while some firms are better off increasing value appropriation, others can improve by specializing in either value creation or value appropriating depending on their current allocation between the two. Geyskens, Gielens, and Dekimpe (2002) demonstrate a positive impact of adding Internet channels, especially for strong companies and early followers.

A special category of capabilities lies in the intangible assets (customers, brands) a firm posses. The value of brands has been addressed in several studies. Brand quality (Aaker and Jacobson, 1994) and attitude (Aaker and Jacobson, 2001) both relate to stock value. Interestingly, work in accounting has found similar results (Amir and Lev, 1996; Barth et al., 1998). Within marketing, Simon and Sullivan (1993) generated a way to deduce the value of a brand by removing the value of fixed assets and using instrumental variables (advertising and order of entry) to capture the value of marketing. The value of brands ranged from close to zero for commodities (e.g., chemical) to 30–50% of the value of tangibles for consumer goods. Mahajan, Rao, and Srivastava (1994) provide a method for assessing the value of a brand in acquisitions. Brand value is clearly linked to stock value (Kerin and Sethuraman, 1998), and changing a brand name has a financial impact (Horsky and Swyngedouw, 1987).

At its simplest level, the value of customers is the expected discounted cash flow from customers in the future which consequently impacts financial performance (Hogan et al., 2002). The cash flow is logically is impacted by marketing actions (Berger et al., 2002, Bolton, Kannan and Branlett, 2000). It depends on three components; acquisition (rate and cost), retention (rate and cost), and expansion/growth in same customer margin (amount and cost). Obviously, aside from cost, the larger the three, the more revenue a firm gets from customers. Although all three matter, the leverage a firm gets from increasing retention appears to be the greatest (Gupta and Lehmann, 2005).

Extensive focus on customers is evident (e.g., Blattberg, Getz, and Thomas, 2001, Gupta and Lehmann, 2005; Reinartz and Kumar, 2000, Rust, Zeithaml and Lemon, 2000). Importantly, the notion of customers is not restricted to final customers. For example, for franchisers or retail chains, the stores play the role of customers, and same-store sales are the equivalent of margin at the individual customer level.

Customer relationship management processes (Hogan, Lemon, and Rust, 2002) have been shown to improve performance (Ramaswami, Bhargava, and Srivastava, 2004; Reinartz, Krafft and Hoyer, 2004). Regarding financial consequences, Kim, Mahajan, and Srivastava (1995) use a customer-based method to evaluate cellular communications companies. Hogan, Lemon, and Labai (2003) focus on the value of a customer in terms of their impact on the diffusion process. Gupta and Lehmann (2003) and Gupta, Lehmann, and Stuart (2004) combine diffusion modeling with the CLV concept to value both dot.com and "regular" (e.g., Capital One) companies.

## Technical and Methodological Issues

### *Cross-Sectional Versus Time Serves Data*

Few impacts are truly instantaneous. Hence, in principle all analysis should be time series in nature. Unfortunately, however, time-series data is often difficult to assemble. Furthermore, the choice of what periodicity to employ (daily, monthly, yearly) impacts the results. Thus, a problem exists concerning the appropriate level of data aggregation and the consequences of using suboptimal ones.

Time-series data allows for testing of the impact of marketing over time. It also raises the issue of whether an effect lasts one period or a few periods (also known as the "dust-settling" period) or is permanent (Dekimpe and Hanseens, 2004). Research suggests that tactics such as promotion and advertising have no long-run (permanent) impact in the vast majority of cases (Dekimpe and Hanseens, 1999).

In terms of metrics, the choice of type of data (as well as the level of aggregation) also impacts the results. For example, Rindfleisch et al. (2004) demonstrated that using cross-sectional versus time-series data sometimes produced noticeably different results.

### *The Impact of Competition*

The impact of competition is often ignored in assessing the impact of marketing. This occurs in part because the modeling complexity of dealing with competition drives many studies to use the "reduced-form" model of "we do X and the result is Y" without trying to capture the process. Another reason for using "myopic" models is data availability. This is a major concern in much CRM work where data typically contains detailed information about customer behavior with respect to one firm but no information about what or how much customers buy elsewhere.

That competition reacts is well established. Recently, considerable effort has gone into adopting the new industrial organization approach to modeling competition (Chintagunta, Kadiyali, and Vilcassim, 2004). One open question is whether incomplete specification of such a model produces better estimates than a myopic model that ignores competition.

### *Subjective Versus Objective Performance Measures*

A potentially important but little considered issue is the nature of the performance metrics that are used. At the most basic level is a distinction between objective and subjective measures. Objective measures such as sales and profits are inherently absolute and hence comparable across as well as within industries. Subjective measures are often employed for reasons of convenience and availability. They can be simple estimates of the "true" objective measure (e.g., "what were sales last year?") which add noise (error) to the analysis and may or may not be biased (i.e., consistently under- or overestimate performance). Alternatively, as is frequently the case, performance measures can be truly subjective (e.g., “how well did your company perform in terms of new product development”). Here the implicit standard of comparison used (e.g., last year’s level, industry average, best in class) will impact results.

One of the earliest projects to systematically relate marketing to performance, the PIMS (Profit Impact of Marketing Strategy) project, relied heavily on relative, subjective measures (i.e., “relative to competition, was your __________ well above average, above average, . . . ?”). This of course raises issues of comparability in cross-industry studies because what is good in one industry may be poor in another.

Ideally, we would always have objective data. Since this is not the case, an interesting question arises concerning what difference it makes. One study that addresses this issue is Ailawadi, Dant, and Grewal (2004). Using concepts such as positivity bias, cognitive consistency, and self-serving attributions, they anticipated a possible mismatch between subjective and objective measures. They examined five years of data on sales agents’ performance collected both by surveys of the agents and archival data. The resulting correlations between subjective and objective measures were in the range of 0.3, and the subjective responses were systematically related to a number of factors such as experience. Since the use of subjective measures is widespread in work on channel partnerships and market orientation as well, future research is needed to calibrate the effect of using subjective measures on links in the model. Although it is unlikely that results using subjective measures are due solely to response style and method effects, it is likely that subjective data leads to overstating the strength of some of the links in the value chain.

## General Issues

### *Comprehensive Testing*

There are two approaches to comprehensively examining the metrics value chain. One is to collect data on all the measures for a sample of companies and to analyze results in a multiple equation model. Although this would clearly be desirable, it involves a level of data collection that is at best difficult.

The other approach is to piece together links, as is sometimes done in meta analyses in the management area. This involves some important technical issues (e.g., correlation matrices assembled this way may not be positive definite, and the correlations may be impacted by peculiar conditions of the study from which they are taken). Still, it seems to be at least a useful starting point for producing the kind of general model that will resonate in boardrooms. In fact, meta analysis appears to be the best way to establish typical measures of the strength of the various links in the chain as well as to uncover important systematic variance in the strength. It also provides a prior which can improve the estimates of links in a particular situation. Thus, meta analysis seems to be the tool of choice for generating general knowledge about links in the chain.

### *Estimating Effects and Action Optimization*

An obvious question is how to optimize marketing activities and budgets. One approach is to develop reduced- form models that link firm actions directly to stock price. Unfortunately, many marketing actions are not likely to produce a measurable change in the stock price (e.g., a promotion for one of P&G’s many brands). Even if the link is clear, the reduced-form model provides little diagnostic information as to the process or time-line by which results emerge (e.g., do promotions increase acquisitions or retention, and what is the time path of the results?).

Another approach is to break the problem down, by separately estimating direct links in the metric value chain. The total effect would then be estimated by multiplying through the links in the chain (as in path analysis). Unfortunately, the variance of the product is the product of the variances, each of which is large at this state of knowledge development. The result is high uncertainty about impacts.

The problem is equally severe for analytical analysis. In addition to uncertainty over links and the impact of the assumptions made, there is the problem of nonlinearity. If all the links are linear, then the optimal level of an action tends to be zero or infinity. On the other hand, nonlinear models are more difficult to estimate and produce even greater variance in estimates.

## Methods for Establishing Links in the Chain

Since in most cases it is hard to establish direct impact on stock performance , it is important to generate knowledge of the effects in the links of the chain. Here we discuss two possible approaches that provide alternatives to the obvious (and useful) "get data and run a regression" method.

### *Persistence Modeling*

One key problem is that it is difficult to assess impacts over time. For example, promotion may have a positive short-run but a negative long-run impact (Mela, Gupta, and Lehmann, 1997). One approach for separating immediate, intermediate ("dust settling") and long-run impacts is persistence modeling (Dekimpe and Hanssens, 2004), a form of time-series modeling. For the most part, these models have been used to assess the impact of marketing actions (primarily promotion and advertising) on product-market performance, in particular sales. Interestingly, one study (Villanueva, Yoo, and Hanssens, 2003a) demonstrated that customer lifetime value is related to the channel by which customers are acquired.

### *Meta Analysis*

As previously mentioned, meta analysis has the potential to facilitate estimating links in the metrics value chain. Links in the chain are likely to differ by situation and to be impacted by modeling, data, and estimation method. This means that the search for a single constant estimate of each link is likely to be fruitless. On the other hand, there may well be a central tendency and key contingencies that account for systematic differences in the links. Hence, by looking across a broad array of situations, empirical generalizations may be uncovered.

Conceptually, this is the basic problem that meta analysis is designed to address (Farley, Lehmann, and Sawyer, 1995; Farley, Hoenig, Lehmann, and Szymanski, 2004). Whether within study (which requires a massive data collection effort by a single team of researchers) or, as is the typical case, cross-study (e.g., based on published research) in nature, the method can establish both the mean size of a link (e.g., the impact of satisfaction on share) and an estimate of how much the link varies under different circumstances (i.e., in monopoly vs. competitive situations).

Of course any meta analysis also has problems, including the representativeness of the available studies and confounding of possible determinants of differences in the results because of the unplanned natural experiment that produced available results. In fact, confounding is common due to a cascade effect in published studies (e.g., a prevalence of studies on consumer goods in the United States using scanner date).

### *Other Approaches*

Of course, time-series analysis and meta analysis are not the only ways to assess links in the chain. For example, if a binary measure such as firm survival or new product success is the focus, hazard modeling approaches can be employed. Basically, these approaches link survival to a number of possible determinants through a hazard function which is similar to a regression model. Two popular uses of hazard models are to assess customer retention and product adoption and sales takeoff (Bowman, 2004).

Another approach is so-called structural modeling (Chintaqunta, Kadiyali, and Vilcasim, 2004). This approach assesses product-market impacts, explicitly taking into account the appropriate (optimal) behavior of competitors.

### *Linking Marketing Directly to Market (Stock) Value*

If you accept stock market value as the ultimate metric, the quest for demonstrating the impact of marketing boils down to two approaches: indirect (through the metrics value chain) or direct. When a marketing activity is a discrete event significant enough to have a measurable impact on stock value (or more precise stock returns), then a direct approach is appropriate. If the impact is immediate and fairly large, then an event study approach is relevant (see Srinivasan and Bharadwaj, 2004, for a concise explanation). The basic idea is that the stock price captures expected future revenue and that change in the stock price reflects anticipated changes in future revenue, in effect instantaneously capturing the value of a change in marketing actions. The basic approach is to compare stock price adjusted for general stock market conditions before and after the event (e.g., a new product introduction) occurs. In practice, issues arise with respect to establishing when the event occurred (or if it occurred gradually), the length of the event "window"—how long a period you use to measure the impact, and how much the pre-event period is impacted by information about the forthcoming event.

Encouragingly, event studies based on daily stock prices have demonstrated significant impact of some marketing actions. Company name changes (Horsky and Swygedouw, 1987) and celebrity endorsements (Agarwal and Kamakura, 1995) generally positively impact stock price, as do new product announcements (Chaney, Devinney, and Winer, 1991; Lane and Jacobson, 1995). Similarly, discrete partner-related activities such as joint ventures and Internet channel additions generated positive movements in stock price (Geysken, Gielens, and DeKimpe, 2002).

Other impacts are less dramatic and occur over time. While this can be handled with long event windows, such windows inevitably are confounded with numerous other changes in the firm, competition, etc. As a consequence, an econometric (regression-like) procedure known as stock return modeling is applicable (Mizik and Jacobson, 2004). Basically, this approach models stock returns as a function of the expected returns, accounting performance (earnings, etc.), and marketing strategy (e.g., market orientation) across a set of firms. The effect of marketing strategy that results from analyzing pooled cross-section, time-series databases have shown significant positive returns to perceived quality (Aaker and Jacobson, 1994), Financial World's brand equity measure, and change in brand attitude for high-tech firms, (Aaker and Jacobson, 2001). Interestingly, the impact of a firm's relative emphasis on R&D versus marketing depends on industry and firm factors (Misik and Jacobson, 2003).

### *Measures Used in Practice*

Several studies have investigated the measures used to assess general marketing performance (Ambler, 2003; Ambler and Kokkinaki, 1997; Bonoma and Clark, 1988; Clark 1999). Many others have focused on more specific aspects such as salesforce performance (e.g., Cravens et al., 1993). One of the most comprehensive studies involves a survey of both marketing and finance executives in the UK (Ambler et al., 2001). Unsurprisingly, financial metrics (profit, margin) were the most frequently measured and most important followed by sales and share.

One question that arises is whether metrics are unique in terms of industry or country. Barwise and Styler (2002) examined which marketing metrics are reported to the board and found that market share and perceived quality were the top two in the United States, Japan, Germany, the UK, and France suggesting that, at least for developed economies, the key metrics are largely global. (Of course, some differences did arise, with the United States more focused on segment profitability and Germany on relative price.)

### Toward a Common Metric Chain

It is clear that special actions and strategies require special metrics. For example, for a new product, it is helpful to have customer ratings of comparisons with substitutes, actual switching patterns and customer ratings of relative advantage, compatibility and risk. Still, considering marketing as a whole, it would be nice to have a common metric chain that could be used in multiple situations both to improve communication with those outside marketing and to force a disciplined look at marketing productivity. As a side benefit, this would create a consistent set of variables against which to assess the impact of various marketing programs and processes. This in turn would help create a database for establishing a set of empirical generalizations of the strength of the links, as well as how the impacts of programs flow from the customer (final and trade) level through product-market results to financial performance and processes, via meta analysis. To that end, Table 6.3 presents a simplified set of measures that flow from customer (final and trade) level through product-market results to financial performance. Because for many firms (including P&G) the critical immediate customer is the channel (e.g., Wal-Mart), a few channel-level metrics are also included.

Of course, not all these measures need be used in all situations. For example, considerable commercial work exists in measuring brand equity (e.g., Y & R's Brand Asset Valuator–BAV, Milward-Browns Brand Z, and Research International Equity Engine). Although these represent multiple constructs, they are highly correlated because of respondent fatigue, halo effects, and the tendency of many variables to vary at the category level more than at the brand level. As a consequence, measures of (1) awareness (presence, knowledge), (2) key associations, (3) overall attitude (preference, liking), (4) attachment (loyalty), and (5) activity (e.g., how frequently they discuss the product) should suffice and largely form a hierarchy. At the product-market level, unit sales and price are key, as is the revenue premium versus generic sales, which serves as a manifest measure of that period's value of the brand (brand equity).

### Summary

Conceptually, it is useful to think of a metrics value chain as the key tool for monitoring marketing actions. Practically, however, it is difficult to estimate all the links in such a chain in a given situation. This suggests the use of information in other situations (i.e., meta analysis) to help estimate the links in a particular case. It also suggests that some type of simulation be done to capture variance in outcomes. For example, by generating pessimistic (assuming the low end of the range for the parameters on each link), best guess, and optimistic scenarios, a better sense of the impact of various marketing actions can be generated.

Table 6.3

**A Basic Marketing Metrics Scorecard**

| Measure | Channel |
|---|---|
| Customer | |
| Awareness | |
| Associations | |
| Attitude | |
| Attachment | |
| Activity | |
| Satisfaction | Satisfaction |
| Willingness to pay/reservation price | Trust |
| Willingness to recommend to a friend | |
| CLV | |
| Product Market | |
| Unit sales/share | Coverage |
| Relative price | Visitations/traffic |
| Revenue premium | Promotion support (featuring/display, etc.) |
| Repeat purchase rates | |
| Growth rate versus market growth rate | |
| Acquisition rate | |
| Acquisition cost | |
| Retention rate | |
| Retention cost | |
| Expansion/same store sales | Margin per channel |
| Financial market | |
| ROI/ROA | |
| Stock returns | |
| Tobin's q | |

Where are we in terms of developing a reasonable consensus on the metrics value chain? Put differently, can we present the equivalent of the Howard–Sheth (1969) model in this area, i.e. a comprehensive view of how various constructs link together? In terms of what the elements of the chain and the links are, there is reasonable convergence around something close to Figure 6.1, although no single chain has the status of, say, CAPM (Capital Asset Pricing Model) in finance. If something like Figure 6.1 becomes widely accepted, several benefits emerge. First, marketing would have a common paradigm to explain itself to those both within and outside the field. Second, the role of different people becomes clear. Psychologically oriented researchers working early in the chain and financially oriented ones working on links to (stock) market performance would complement each other rather than compete. Finally, we can begin to collect information on the links in the chain across situations to establish general patterns. Such patterns facilitate disciplined thinking and budgeting (i.e., if a budget implies strength of effects 10 times the top of the range of previous results, some serious questioning of the assumptions is called for).

Where are we in terms of generating empirical generalizations about the various links? Sadly, we are not very far along. Although some links have a history of study that already have or could be turned into specific parameter estimates for the strength of the links, many others do not (see Table 6.4). Importantly, most of the estimates available are based on linking two of the elements only, the equivalent of simple correlations. This underspecification leads to potential problems and biases in the results. Thus, in addition to more studies linking particular elements in the chain, comprehensive studies are needed which estimate the entire chain in a multi-equation model framework.

Table 6.4

**The Current State of Knowledge**

Areas where current knowledge provides specific estimates of links
- Advertising spending to sales
- Price to sales
- The pattern of new product diffusion (sales)
- Promotion to short-run sales
- Satisfaction to financial results

Links where more knowledge is needed
- Company action to competitive action *and* vice-versa
- Product-market results to financial performance
- Satisfaction to consumer behavior (repeat rates)
- The impact of environmental influences

## Appendix 6.1 **Some Common Metrics**

| | | |
|---|---|---|
| **1. Customer** | Mind-Set | Awareness |
| | | Perceptions |
| | | Attitudes |
| | | Intentions |
| | | Loyalty |
| | Behavior | Recovery |
| | | Frequency |
| | | Spending |
| | | Acquisition Rate and Cost |
| | | Retention |
| | | Expansion |
| | | Customer Lifetime Value (CLV) |
| | | Switching Pattern |
| | | Cost of Retention |
| | | Activity (Word of Mouth) |
| **2. Strategy and Capabilities** | Orientation: Market, Customer, Competitor | |
| | R&D/Product Development | Spending |
| | | Output Level |
| | | Time to Market |
| **3. Marketing Activities** | Advertising | Firm Measure |
| | | Budget |
| | | Media |
| | | Scheduling and Placement |
| | | Copy |
| | | Response/Elasticity |

| | | |
|---|---|---|
| | Product | Quality |
| | Price | Average Customer Price |
| | | Price to Trade |
| | | % on Deal; Average Deal % |
| | | Relative Price |
| | | Elasticity |
| | Promotion | Incremental Sales |
| | | ROI |
| | Place | Distribution Coverage |
| | | Sales per (Outlet, Facing, . . . ) |
| | Service | Time to Service |
| | | Satisfaction |
| | Web | Hits/Visits |
| | | Report Use |
| | | "Stickiness" |
| | | Sales and Profits |
| **4. Partner** | Channel Support | Spending |
| | | Carrying (ACV) |
| | Commitment | |
| | Trust | |
| | Information Sharing | |
| **5. Employee (esp. Customer Contact)** | | |
| | Motivation | |
| | Job Satisfaction | |
| | Productivity (e.g., Conversion Rate, Salesperson Calls per Day) | |
| **6. Product Market** | Sales | |
| | Share (of Market, Requirements, Wallet) | |
| | Price | |
| | Price Premium | |
| | Revenue Premium | |
| **7. Financial Market** | Financial Reporting Based | ROI, ROA, . . . |
| | | EVA |
| | Stock Market Based | Stock Price |
| | | MVA |
| | | Tobin's q |

## References


Aaker, David A., and Robert Jacobson. (1994) "The Financial Information Content of Perceived Quality." *Journal of Marketing,* 58 (May), 191–201.

———. (2001) "The Value Relevance of Brand Attitude in High-Technology Markets." *Journal of Marketing Research,* 38 (November), 485–549.

Agarwal, Jagdish, and Wagner A. Kamakura. (1995) "The Economic Worth of Celebrity Endorsers: An Event Study Analysis." *Journal of Marketing,* 59 (3), 56–62.

Ailawadi, Kusum, Norm Borin, and Paul Farris. (1995) "Market Power and Performance: A Cross-Industry Analysis of Manufacturers and Retailers." *Journal of Retailing,* 71 (3), 211–248.

Ailawadi, Kusum, Rajir P. Dant, and Dhnur Grewal. (2004) "The Difference Between Perceptual and Objective Performance Measures: An Empirical Analysis." MSI Working Paper 04–103.

Ailawadi, Kusum L., Donald R. Lehmann, and Scott A. Neslin. (2001) "Market Response to a Major Policy Change in the Marketing Mix: Learning from Procter and Gamble's Value Pricing Strategy." *Journal of Marketing,* 65 (January), 44–61.

———. (2003) "Revenue Premium as an Outcome Measure of Brand Equity." *Journal of Marketing,* 67 (October), 1–17.

Allenby, Greg, and Dominique Hanssens. (2004) Advertising Response. MSI Report 05-200a.

Ambler, Tim. (2003) *Marketing and the Bottom Line: The New Metrics of Corporate Wealth.* 2d ed. London: Financial Times/Prentice Hall, Pearson Education.

Ambler, Tim, and Patrick Barwise. (1998) "The Trouble with Brand Valuation." *Journal of Brand Management,* 5 (May), 367–377.

Ambler, Tim, and Flora Kokkinaki. (1997) "Measures of Marketing Success." *Journal of Marketing Management,* 13, 7–18.

———. (1998) "Marketing Performance Measurement: Which Way Is Up?" In *Performance Measurement: Theory and Practice,* ed. A.D. Neely and D.B. Waggoner. Cambridge: Cambridge University Press.

Ambler, Tim, Flora Kokkinaki, Stefano Puntoni, and Debra Riley. (2001) Assessing Market Performance: The Current State of Metrics. Working paper, London Business School.

Amir, Eli, and Baruch Lev. (1996) "Value Relevance of Non-Financial Information: The Wireless Communication Industry." *Journal of Accounting and Economics,* 22 (1–3), 13–20.

Anderson, Eugene W., Claes Fornell, and Donald R. Lehmann. (1994) "Customer Satisfaction, Market Share, and Profitability: Findings from Sweden." *Journal of Marketing,* 58, 53–66.

Anderson, Eugene W., Claes Fornell, and Sanal K. Mazvancheryl. (2004) "Customer Satisfaction and Shareholder Value." *Journal of Marketing,* 68 (October), 172–185.

Anderson, Eugene W., Claes Fornell, and Roland Rust. (1997) "Customer Satisfaction, Productivity, and Profitability: Differences Between Goods and Services." *Marketing Science,* 16 (2), 129–145.

Anderson, Eugene W., and V. Mittal. (2000) "Strengthening the Satisfaction-Profit Chain." *Journal of Service Research,* 3, 107–120.

Assmus, Gert, John U. Farley, and Donald R. Lehmann. (1984) "How Advertising Affects Sales: Meta-Analysis of Econometric Results." *Journal of Marketing Research,* 21, 65–74.

Barth, M.E., M. Clement, G. Foster, and R. Kasznik. (1998) "Brand Values and Capital Market Valuation," *Review of Accounting Studies,* 3 (1), 41–68.

Barwise, Patrick, and Alany Styler. (2002) *Marketing Expenditure Trends.* London: London Business School.

Bass, Frank M. (1969) "A New Product Growth Model for Consumer Durables." *Management Science,* 15 (January), 215–227.

Batra, Rajeev, Donald R. Lehmann, Joanne Burke, and Jae Pae. (1995) "When Does Advertising Have an Impact? A Study of Tracking Data." *Journal of Advertising Research,* 35 (September–October), 19–32.

Berger, Paul D., and Nada I. Nasr. (1998) "Customer Lifetime Value: Marketing Models and Applications." *Journal of Interactive Marketing,* 12 (1), 17–30.

Berger, Paul D., Ruth N. Bolton, Douglas Bowman, Elten Briggs, et al. (2002) "Marketing Actions and the Value of Customer Assets: A Framework for Customer Asset Management." *Journal of Service Research,* 5 (1; August), 39–54.

Bernhardt, Kenneth, Naveen Donthu, and Pamela Kennet. (2000) "A Longitudinal Analysis of Satisfaction and Profitability." *Journal of Business Research,* 47 (2), 161–171.

Blattberg, Robert, and John Deighton. (1996) "Manage Marketing by the Customer Equity Test." *Harvard Business Review,* 75 (4), 136–144.

Blattberg, Robert, Gary Getz, and Jacquelyn S. Thomas. (2001) C*ustomer Equity: Building and Managing Relationships as Valuable Assets.* Boston, MA: Harvard Business School Press.

Bolton, Ruth, P.K. Kannan, and Matthew Branlett. (2000) "Implications of Loyalty Program Membership and Service Experiences for Customer Retention and Value." *Journal of the Academy of Marketing Science,* 28 (1), 95–108.

Bonoma, Thomas V., and Bruce C. Clark. (1988) *Marketing Performance Assessment.* Boston: Harvard Business School Press.

Boulding, William, Ajay Kalra, Richard Staelin, and Valarie Zeithaml. (1993) "A Dynamic Process Model of Service Quality: From Expectations to Behavioral Intentions." *Journal of Marketing Research,* 30 (February), 7–27.

Bowman, Douglas. (2004) "Survival Models for Marketing Strategy." In *Assessing Marketing Strategy Performance,* ed. Christine Moorman and Donald R. Lehmann, pp. 115–143. Cambridge, MA: Marketing Science Institute.

Bucklin, Randolph E., Donald R. Lehmann, and John D.C. Little. (1998) "From Decision Support to Decision Automation: A 2020 Vision." *Marketing Letters,* 9 (August), 235–246.

Buzzell, Robert D., and Bradley Gale. (1987) *The PIMS Principles: Linking Strategy to Performance.* New York: The Free Press.

Capon, Noel, John U. Farley, and Scott Hoenig. (1990) "Determinants of Financial Performance: A Meta-Analysis." *Management Science,* 36 (October), 1143–1159.

Chaney, Paul K., Timothy M. Devinney, and Russell S. Winer. (1991) "The Impact of New Product Introductions on the Market Value of Firms." *Journal of Business,* 64 (4), 573–610.

Chauvin, Keith W., and Mark Hirschey. (1993) "Advertising, R and D Expenditures, and the Market Value of the Firm." *Financial Management,* 22 (4), 128–140.

Cheng, C.S. Agnes, and J.P. Charles Chen. (1997) "Firm Valuation of Advertising Expense: An Investigation of Scalar Effects." *Managerial Finance,* 23 (10), 41–62.

Chintagunta, Pradeep K., Vrinda Kadiyali, and Naufel J. Vilcassim. (2004) "Structural Models of Competition: A Marketing Strategy Perspective." In *Assessing Marketing Strategy Performance,* ed. Christine Moorman and Donald R. Lehmann, pp. 95–114. Cambridge, MA: Marketing Science Institute.

Clark, Bruce H. (1999) "Marketing Performance Measures: History and Interrelationships." *Journal of Marketing Management,* 15 (8; November), 711–732.

Cleland, Alan S., and Albert V. Bruno. (1996) *Market Value Process: Bridging Customer and Shareholder Value.* San Francisco: Jossey-Bass.

Cloninger, Dale O., Raj Aggarwal, Jonathan Karpoff, Nelson J. Lacey, and Clifford Smith. (2000) "Doing Well by Doing Good: Do Financial Markets 'Price' Ethical Behavior?" *Financial Practice and Education,* (Fall–Winter), 24–33.

Cooper, Robert G. (1984) "How New Product Strategies Impact on Financial Performance." *Journal of Product Innovation Management,* 1 (1), 5–18.

Cravens, David W., Thomas N. Ingram, Raymond W. LaForge, and Clifford E. Young. (1993) "Behavior-Bases and Outcome-Based Sales Force Control Systems." *Journal of Marketing,* 57 (October), 47–59.

Day, George, and Liam Fahey. (1988) "Valuing Marketing Strategies." *Journal of Marketing,* 52 (3; July), 45–57.

Dekimpe, Marnik, and Dominique Hanssens. (1995) "The Persistence of Marketing Effects on Sales." *Marketing Science,* 14 (1; Winter), 1–21.

———. (1999) "Sustained Spending and Persistent Response: A New Look at Long-Term Marketing Profitability." *Journal of Marketing Research,* 3 (4; November), 1–31.

———. (2004) "Persistence Modeling for Assessing Marketing Strategy Performance." In *Assessing Marketing Strategy Performance,* ed. Christine Moorman and Donald R. Lehmann, pp. 69–94. Cambridge, MA: Marketing Science Institute.

Despande, Rohit, John Farley, and Frederick Webster. (1993) "Corporate Culture, Customer Orientation and Innovativeness in Japanese Firms: A Quadrad Analysis" *Journal of Marketing*, 57 (January), 23–37.

Despande, Rohit, and Frederick E. Webster, Jr. (1989) "Corporate Culture, Customer Orientation, and Innovativeness in Japanese Firms: A Quadrad Analysis." *Journal of Marketing,* 52 (January), 23–36.

Doukas, John, and Lorne Switzer. (1992) "The Stock Market's Valuation of R and D Spending and Market Concentration." *Journal of Economics and Business,* 44, 95–114.

Doyle, Peter. (2000a) *Value-Based Marketing: Marketing Strategies for Corporate Growth and Shareholder Value.* New York: John Wiley and Sons.

———. (2000b) "Valuing Marketing's Contribution." *European Management Journal,* 18 (3), 232–245.
Dutta, Shantanu, Chakravarti Narashimhan, and Surendra Rajiv. (1999) "Success in High Technology Markets: Is Marketing Capability Critical?" *Marketing Science*, 18 (4), 547–568.
Eastlack, Joseph O., Jr., and Ambar G. Rao. (1986) "Modeling Response to Advertising and Pricing Changes for 'V-8' Cocktail Vegetable Juice." *Marketing Science,* 5 (Summer), 245–259.
Eddy, A., and G. Saunders. (1980) "New Product Announcements and Stock Prices." *Decision Sciences,* 11, 90–97.
Erdem, Tulin, and Baohong Sun. (2002) "An Empirical Investigation of the Spillover Effects of Advertising and Sales Promotions in Umbrella Branding." *Journal of Marketing Research,* 39 (November), 408–420.
Erickson, Gary, and Robert Jacobson. (1992) "Gaining Competitive Advantage Through Discretionary Expenditures: The Returns to R and D and Advertising." *Management Science,* 38, 1264–1279.
Farley, John U., Scott Hoenig, Donald R. Lehmann, and David M. Szymanski. (2004) "Assessing the Impact of Marketing Strategy Using Meta-Analysis." In *Assessing Marketing Strategy Performance,* ed. Christine Moorman and Donald R. Lehmann, pp. 145–164. Cambridge, MA: Marketing Science Institute.
Farley, John, Donald R. Lehmann, and Alan Sawyer. (1995) "Empirical Marketing Generalizations Using Meta-Analysis." *Marketing Science*, 14 (September), 636–646.
Fornell, Claes, Sunil Mithas, Forrest Morgeson, and M.S. Krishnan. (2004) Customer Satisfaction and Stock Prices. Working paper, University of Michigan.
Gatignon, Hubert, Jehoshua Eliashberg, and Thomas S. Robertson. (1989) "Modeling Multinational Diffusion Patterns: An Efficient Methodology." *Marketing Science,* 8 (3), 231–247.
Geyskens, Inge, Katrijn Gielens, and Marnik G. Dekimpe. (2002) "The Market Valuation of Internet Channel Additions." *Journal of Marketing,* 66 (2), 102–119.
Geyskens, Inge, Jan-Benedict E.M. Steenkamp, and Nirmalya Kumar. (1998) "Generalizations About Trust in Marketing Channel Relationships Using Meta-Analysis." *International Journal of Research in Marketing,* 15 (3), 223–248.
Goldenberg, Jacob, Barak Libai, and Eitan Muller. (2004) "Complex Yet Simple: Cellular Automata as an Enabling Technology in Marketing Strategy Research." In *Assessing Marketing Strategy Performance*, ed. Christine Moorman and Donald R. Lehmann, pp. 229–246. Cambridge, MA: Marketing Science Institute.
Golder, Peter N., and Gerard J. Tellis. (1993) "Pioneer Advantage: Marketing Logic or Marketing Legend?" *Journal of Marketing Research,* 30 (May), 158–170.
———. (1997) "Will It Ever Fly? Modeling the Takeoff of Really New Consumer Durables." *Marketing Science,* 16 (3), 256–270.
Graham, Roger C., and Kristina D. Frankenberger. (2000) "The Contribution of Changes in Advertising Expenditures to Earnings and Market Values." *Journal of Business Research,* 50 (2), 149–155.
Greenley, Gordon E. (1995) "Market Orientation and Company Performance: Empirical Evidence from UK Companies." *British Journal of Management,* 6, 1–13.
Gupta, Sunil, and Donald R. Lehmann. (2003) "Customers as Assets." *Journal of Interactive Marketing,* 17 (1; Winter), 9–24.
Gupta, Sunil, and Donald R. Lehmann. (2005) *Managing Customers as Investments*. Wharton Publishing/ Pearson-Financial Times.
Gupta, Sunil, Donald R. Lehmann, and Jennifer Ames Stuart. (2004) "Valuing Customers." *Journal of Marketing Research,* 41 (1; February), 7–18.
Gupta, Sunil, and Valarie Zeithaml. (2005) Customer Satisfaction, Customer Value, and Customer Metrics: A Review and Future Research Agenda. MSI Report 05-200c.
Hallowell, R. (1996) "The Relationship of Customer Satisfaction, Customer Loyalty, and Profitability: An Empirical Study." *International Journal of Service Industry Management,* 7 (4), 27–42.
Harris, Lloyd C. (2001) "Market Orientation and Performance: Objective and Subjective Empirical Evidence from UK Companies." *Journal of Management Studies,* 38 (1), 17–43.
Hauser, John, Gerard J. Tellis, and Abbie Griffin. (2004) Research on Innovation: A Review and Agenda for Marketing. MSI Report 05-200f.
Hendricks, K.D., and V.R. Singhal. (1996) "Quality Awards and the Market Value of the Firm: An Empirical Investigation." *Management Science,* 42 (March), 415–436.
Heskett, James L., Thomas O. Jones, Gary W. Loveman, W. Earl Sasser, Jr., and Leonard Schlesinger. (1994) "Putting the Service-Profit Chain to Work." *Harvard Business Review,* 72 (2), 164–174.

Hirschey, Mark. (1982) "Intangible Capital Aspects of Advertising and R and D Expenditures." *Journal of Industrial Economics,* 30 (June), 375–390.

Hogan, John E., Donald R. Lehmann, Maria Merino, Rajendra K. Srivastava, Jacquelyn S. Thomas, and Peter C. Verhoef. (2002) "Linking Customer Assets to Financial Performance." *Journal of Service Research,* 5 (1; August), 26–38.

Hogan, John E., Katherine N. Lemon, and Barak Libai. (2003) "What Is the True Value of a Lost Customer?" *Journal of Service Research,* 5 (3; February), 196–208.

Hogan, John E., Katherine N. Lemon, and Roland T. Rust. (2002) "Customer Equity Management: Charting New Direction for the Future of Marketing." *Journal of Service Research,* 5 (1), 4–12.

Homburg, Christian, and Christian Pflesser. (2000) "A Multiple-Layer Model of Market-Oriented Organizational Culture: Measurement Issues and Performance Outcomes." *Journal of Marketing,* 37 (November), 449–462.

Horsky, Dan, and Patrick Swyngedouw. (1987) "Does It Pay to Change Your Company's Name? A Stock Market Perspective." *Marketing Science,* (Fall), 320–335.

Howard, John A., and Jagdish Sheth. (1969) *The Theory of Buyer Behavior.* New York: John Wiley and Sons.

Ittner, Christopher D., and David F. Larcker. (1996) "Measuring the Impact of Quality Initiatives on Firm Financial Performance." In *Advances in the Management of Organizational Quality,* 1, ed. Soumen Ghosh and Donald Fedor, pp. 1–37. Greenwich, CT: JAI.

———. (1998) "Are Non-financial Measures Leading Indicators of Financial Performance? An Analysis of Customer Satisfaction." *Journal of Accounting Research,* 36 (Supplement), 1–35.

Jarrell, Gregg, and Sam Peltzman. (1985) "The Impact of Product Recalls on the Wealth of Sellers." *Journal of Political Economy,* 93 (3), 512–536.

Jose, Manuel L., Len M. Nichols, and Jerry L. Stevens. (1986) "Contributions of Diversification, Promotion, and R and D to the Value of Multi Product Firms: A Tobin's *q* Approach." *Financial Management,* 15 (4), 33–42.

Joshi, Amit, and Dominique M. Hanssens. (2004) Advertising Spending and Market Capitalization. Working paper, UCLA Marketing Studies Center.

Kallapur, Sanjey, and Sabrina Y.S. Kwan. (2004) "The Value Relevance and Reliability of Brand Assets Recognized by UK Firms." *Accounting Review,* 79 (January), 151–172.

Kalyanaram, Gurumurthy, William T. Robinson, and Glen L. Urban. (1995) "Order of Market Entry: Established Empirical Generalizations, Emerging Empirical Generalizations, and Future Research." *Marketing Science,* 14 (3), G212–221.

Kamakura, Wagner A., Vikas Mittal, Fernando de Rosa, and Jose Alfonso Mazzon. (2002) "Assessing the Service Profit Chain." *Marketing Science,* 21 (3), 294–317.

Kamakura, W.A., and G.J. Russell. (1993) "Measuring Brand Value with Scanner Data." *International Journal of Research in Marketing,* 10 (April), 9–22.

Kaplan, Roberts, and David P. Norton. (1996) *The Balanced Scorecard*. Boston: Harvard Business School Press.

Kaul, Anil, and Dick R. Wittink. (1995) "Empirical Generalizations About the Impact of Advertising on Price Sensitivity and Price." *Marketing Science,* 14 (3), G151–160.

Keller, Kevin Lane, and Donald R. Lehmann. (2005) Brands and Branding: Research Findings and Future Priorities. MSI Report 05-200b.

Kerin, R.A., and R. Sethuraman. (1998) "Exploring the Brand Value-Shareholder Value Nexus for Consumer Goods Companies." *Journal of the Academy of Marketing Science,* 26 (4), 260–273.

Kevin Lane, and Donald R. Lehmann. (2003) "The Brand Value Chain: Optimizing Strategic and Financial Brand Performance." M*arketing Management,* (May/June), 26–31.

Kim, Namwoon, Vijay Mahajan, and Rajendra K. Srivastava. (1995) "Determining the Going Value of a Business in an Emerging Information Technology Industry: The Case for Cellular Communications Industry." *Technological Forecasting and Social Change,* 49 (3; July), 257–279.

Kirplani, V.A., and Stanley S. Shapiro. (1973) "Financial Dimensions of Marketing Management." *Journal of Marketing,* 37 (July), 40–49.

Kohli, Ajay K., and Bernard J. Jaworski. (1990) "Market Orientation: The Construct, Research Propositions, and Managerial Implications." *Journal of Marketing,* 54 (2), 1–18.

Koku, Paul S., Harsharanjeet S. Jagpal, and P.V. Viswanath. (1997) "The Effect of New Product Announcements and Preannouncements on Stock Price." *Journal of Market-Focused Management,* 2 (November), 183–199.

Kopalle, Praveen K., and Donald R. Lehmann. (1995) "The Effects of Advertised and Observed Quality on Expectations About New Product Quality." *Journal of Marketing Research,* 32 (August), 280–290.

———. (2001) "Strategic Management of Expectations: The Role of Disconfirmation Sensitivity and Perfectionism." *Journal of Marketing Research,* 38 (August), 386–394.

Kumar, Pryash. (1999) "The Impact of Long-Term Client Relationships on the Performance of Business Service Firms." *Journal of Services Research,* 2 (August), 4–18.

Lane, Vicki, and Robert Jacobson. (1995) "Stock Market Reactions to Brand Extension Announcements: The Effects of Brand Attitude and Familiarity." *Journal of Marketing,* 63 (Special Issue), 180–197.

Lee, P. Ruby, and Rajdeep Grewal. (2003) "Strategic Response to New Technologies and Their Impact on Firm Performance." *Journal of Marketing,* 68 (October), 157–171.

Lehmann, Donald R. (2004) "Metrics for Making Marketing Matter." *Journal of Marketing,* 68 (October), 73–75.

Lodish, Leonard M., Magid Abraham, S. Kalmenson, J. Livelsberger, Beth Lubetkin, B. Richardson, and M.E. Stevens. (1995) "How TV Advertising Works: A Meta-Analysis of 389 Real World Split Cable TV Advertising Experiments." *Journal of Marketing Research,* 32 (May), 125–139.

Loveman, Gary W. (1998) "Employee Satisfaction, Customer Loyalty, and Financial Performance: An Empirical Examination of the Service Profit Chain in Retail Banking," *Journal of Service Research,* 1 (1), 18–31.

Lusch, Robert F., and Nicholas S.P. Tay. (2004) "Agent-Based Modeling: Gaining Insight into Firm and Industry Performance." In *Assessing Marketing Strategy Performance,* ed. Christine Moorman and Donald R. Lehmann, pp. 213–228. Cambridge, MA: Marketing Science Institute.

Mahajan, V., V.R. Rao, and R.K. Srivastava. (1994) "An Approach to Assess the Importance of Brand Equity in Acquisition Decisions." *Journal of Product Innovation Management,* 11 (3), 2221–2235.

Mathur, Lynette K., and Ike Mathur. (1995) "The Effect of Advertising Slogan Changes on the Market Values of Firms." *Journal of Advertising Research,* 35 (1), 59–65.

Mela, Carl F., Sunil Gupta, and Donald R. Lehmann. (1997) "The Long-Term Impact of Promotion and Advertising on Consumer Brand Choice." *Journal of Marketing Research,* 34 (2), 248–261.

Merino, Maria, Raji Srinivasan, and Rajendra Srivastava. (2003) Impact of Advertising on Business Performance and Volatility. Working paper, University of Texas.

Miyazaki, A.D., and A.G. Morgan. (2001) "Assessing Market Value of Event Sponsoring: Corporate Olympic Sponsorships." *Journal of Advertising Research,* 41 (January–February), 9–15.

Mizik, Natalie and Robert Jacobson. (2003) "Trading Off Between Value Creation and Value Appropriation: The Financial Implication of Shifts in Strategic Emphasis." *Journal of Marketing,* 67 (January), 63–76.

———. (2004) "Stock Return Response Modeling." In *Assessing Marketing Strategy Performance,* ed. Christine Moorman and Donald R. Lehmann, pp. 29–46. Cambridge, MA: Marketing Science Institute.

Moorman, Christine and Donald R. Lehmann. (2004) *Assessing Marketing Strategy Performance.* Cambridge, MA: Marketing Science Institute.

Moorman, Christine, Rohit Deshpande, and Gerald Zaltman. (1993) "Factors Affecting Trust in Market Relationships." *Journal of Marketing,* 57 (January), 81–101.

Moorman, Christine, Gerald Zaltman, and Rohit Deshpande. (1992) "Relationships Between Providers and Users of Market Research: The Dynamics of Trust Within and Between Organizations." *Journal of Marketing Research,* 29 (August), 314–329.

Narayanan, Sridhar, Ramarao Desiraju, and Pradeep K. Chintagunta. (2004) "Return on Investment Implications for Pharmaceutical Promotional Expenditures: The Role of Marketing Mix Interactions." *Journal of Marketing,* 68 (October), 90–105.

Narver, John C., and Stanley F. Slater. (1990) "The Effect of a Market Orientation on Business Profitability." *Journal of Marketing,* 54 (October), 20–35.

Nayyar, Praveen P. (1995) "Stock Market Reaction to Customer Service Changes." *Strategic Management Journal,* 16 (January), 39–54.

Nelson, Eugene, Roland T. Rust, Anthony Zahorik, Robin L. Rose, Paul Batalden, and Beth Siemanski. (1992) "Do Patient Perceptions of Quality Relate to Hospital Financial Performance?" *Journal of Healthcare Marketing,* 12 (December), 1–13.

Neslin, Scott A. (2002) *Sales Promotion.* Cambridge, MA: Marketing Science Institute.

Nijs, Vincent R., Marnik G. Dekimpe, Jan-Benedict E.M. Steenkamp, and DominiqueM. Hanssens. (2001) "The Category-Demand Effects of Price Promotions." *Marketing Science,* 20 (1), 1–22.

Oliver, Richard. (1997) *Satisfaction: A Behavioral Perspective on the Consumer.* New York: McGraw-Hill.

Parasuraman, A., Valarie A. Zeithaml, and Leonard L. Berry. (1994) "Reassessment of Expectations as a Comparison Standard in Measuring Service Quality: Implications for Further Research." *Journal of Marketing,* 58 (January), 111–124.

———. (1998) "SERVQUAL: A Multiple-Item Scale for Measuring Consumer Perceptions of Service Quality." *Journal of Retailing,* 64 (Spring), 12–40.

Pardue, J. Harold, Eric Higgins, and Tim Biggart. (2000) "The Impact of New Product Announcements on Firm Value in Information Technology Producing Industries: An Examination of Industry-Level Evolutionary Eras." *The Engineering Economist,* 45 (2), 144–157.

Pauwels, Koen, Jorge Silva-Risso, Shuba Srinivasan, and Dominique M. Hanssens. (2004) "New Products, Sales Promotions, and Firm Value: The Case of the Automobile Industry." *Journal of Marketing,* 68 (October), 142–156.

Pelham, Alfred M. (1999) "Influence of Environment, Strategy, and Market Orientation on Performance in Small Manufacturing Firms." *Journal of Business Research,* 45 (1), 33–46.

Pelham, Alfred M., and David T. Wilson. (1996) "A Longitudinal Study of the Impact of Market Structure, Firm Structure, Strategy, and Market Orientation Culture on Dimensions of Small Firm Performance." *Journal of the Academy of Market Science,* 24 (1), 27–43.

Ramaswami, Sridhar N., Mukesh Bhargava, and Rajendra Srivastava. (2004) Market-Based Assets and Capabilities, Business processes, and Financial Performance. MSI Working Paper Series, #04–102.

Rao, Vithala R., Manoj K. Agarwal, and Denise Dahlhoff. (2004) "How Is Manifest Branding Strategy Related to the Intangible Value of a Corporation?" *Journal of Marketing,* 68 (October), 126–41.

Reichheld, Frederick F., and Thomas Teal. (1996) *The Loyalty Effect.* Boston: Harvard Business School Press.

Reinartz, Werner, Manfred Krafft, and Wayne D. Hoyer. (2004) "The Customer Relationship Management Process: Its Measurement and Impact on Performance." *Journal of Marketing Research,* 61 (August), 293–305.

Reinartz, Werner, and V. Kumar. (2000) "On the Profitability of Long-Life Customers in a Noncontractual Setting: An Empirical Investigation and Implications for Marketing," *Journal of Marketing,* 64 (4; October), 17–35.

———. (2004) "A Customer Lifetime Value Framework for Customer Selection and Optimal Resource Allocation Strategy." *Journal of Marketing,* 68 (October), 106–125.

Rindfleisch, Aric, Alan Malter, Shankar Ganesan, and Christine Moorman. (2004) Cross-Sectional vs. Longitudinal New Product Outcomes. Working paper, University of Wisconsin.

Riskey, Dwight R. (1997) "How T.V. Advertising Works: An Industry Response." *Journal of Marketing Research,* 34 (2; May), 292–293.

Rust, Roland T., Tim Ambler, Gregory S. Carpenter, V. Kumar, and Rajendra K. Srivastava. (2004) "Measuring Marketing Productivity: Current Knowledge and Future Directions." *Journal of Marketing,* 68 (October), 76–89.

Rust, Roland, Katherine Lemon, and Valarie Zeithaml. (2000) *Driving Customer Equity: How Customer Lifetime Value Is Reshaping Corporate Strategy.* New York: The Free Press.

———. (2004) "Return on Marketing: Using Customer Equity to Focus Marketing Strategy." *Journal of Marketing,* 68 (1; January), 109–126.

Rust, Roland T., Christine Moorman, and Peter R. Dickson. (2002) "Getting Return on Quality: Cost Reduction, Revenue Expansion, or Both?" *Journal of Marketing,* 66 (October), 7–24.

Rust, Roland, and Anthony Zahorik. (1993) "Customer Satisfaction, Customer Retention, and Market Share." *Journal of Retailing,* 69 (Summer), 193–215.

Rust, Roland, Anthony Zahorik, and Timothy Keiningham. (1995) "Return on Quality (ROQ): Making Service Quality Financially Accountable." *Journal of Marketing,* 59 (April), 58–70.

Rust, Roland T., Valarie A. Zeithaml, and Katherine N. Lemon. (2000) *Driving Customer Equity: How Customer Lifetime Value Is Reshaping Corporate Strategy.* New York: The Free Press.

Schmittlein, David, Donald Morrison, and Richard Colombo. (1987) "Counting Your Customers: Who Are They and What Will They Do Next?" *Management Science,* 33 (1; January), 1–24.

Sethuraman, Raj. (1995) "A Meta-Analysis of National Brand and Store Brand Cross-Promotional Price Elasticities." *Marketing Letters,* 6 (4), 275–286.

Sethuraman, Raj, and Gerald J. Tellis. (1991) "An Analysis of the Tradeoff Between Advertising and Price Discounting." *Journal of Marketing Research,* 28 (2; May), 160–174.

Simon, Carol J. and Mary W. Sullivan. (1993) "The Measurement and Determinants of Brand Equity: A Financial Approach." *Marketing Science,* 12 (Winter), 28–52.

Slater, Stanley F., and John C. Narver. (1994) "Does Competitive Environment Moderate the Market Orientation-Performance Relationship?" *Journal of Marketing,* 58 (January), 46–55.

Srinivasan, Raji, and Sundar Bharadwaj. (2004) "Event Studies in Marketing Strategy Research." In *Assessing Marketing Strategy Performance,* ed. Christine Moorman and Donald R. Lehmann, pp. 9–28. Cambridge, MA: Marketing Science Institute.

Srivastava, Raj and David J. Reibstein (2004) Metrics for Linking Marketing to Financial Performance. MSI Reports 05-200e.

Srivastava, Rajendras, T.H. Moinesh, R. Wood, and A.J. Caprano. (1999) "The Value of Corporate Reputation: Evidence from the Equity Market." *Corporate Reputation Review,* 1 (1), 62–68.

Srivastava, R.K. T.A. Shervani, and Liam Fahey. (1998) "Market-Based Assets and Shareholder Value: A Framework for Analysis." *Journal of Marketing,* 62 (1; January), 2–18.

Sultan, Fareena, John U. Farley, and Donald R. Lehmann. (1990) "A Meta-Analysis of Applications of Diffusion Models." *Journal of Marketing Research,* 27 (February), 70–77.

Szymanski, David M., Lisa C. Troy, and Sundar G. Bharadwaj. (1995) "Order of Entry and Business Performance: An Empirical Synthesis and Reexamination." *Journal of Marketing,* 59 (October), 17–33.

Tellis, Garard J., Stefan Stremersch, and Eden Yin. (2003) "The International Takeoff of New Products: Economics, Culture, and Country Innovativeness." *Marketing Science,* 22 (Spring), 188–208.

Vakratsas, Demetrios, and Tim Ambler. (1999) "How Advertising Works: What Do We Really Know?" *Journal of Marketing,* 63 (January), 26–43.

Villaneuva, Julian, Shijin Yoo, and Dominique M. Hanssens. (2003a) Customer Acquisition Channels and Customer Equity: A Long-Run View. Working paper, UCLA, Anderson Graduate School of Management.

———. (2003b) The Impact of Acquisition Channels on Customer Equity. Working paper, UCLA.

Zeithaml, Valarie A. (2000) "Service Quality, Profitability, and the Economic Worth of Customers: What We Know and What We Need to Learn." *Journal of the Academy of Marketing Science,* 28 (1), 67–85.

Zeithaml, Valarie A. and A. Parasuraman. (2004) *Service Quality.* Cambridge, MA: MSI Relevant Knowledge Series.

CHAPTER 7

# MULTILEVEL, HIERARCHICAL LINEAR MODELS AND MARKETING

## This Is Not Your Adviser's OLS Model

JAMES L. OAKLEY, DAWN IACOBUCCI, AND ADAM DUHACHEK

**Abstract**

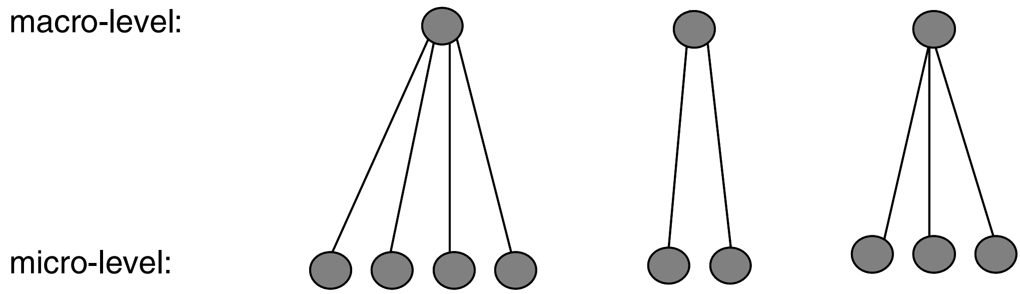
*This chapter provides an introduction to hierarchical linear modeling (HLM) for marketing researchers. We begin by motivating why one might use HLM models, describing what they are and what research questions they can address. We then describe the techniques. We illustrate the models on a small data set, and we instruct potential adopters on how to fit the models via existing software so that the reader should be able to reproduce the results we present in this chapter. We also present findings from a larger, real data set to illustrate the substantive insights that may be gleaned from these models.*

Hierarchical linear modeling (HLM) is a data analysis tool that is becoming increasingly important in a number of social sciences, including marketing. In this chapter, we introduce the basic HLM models. We begin by describing the sorts of research questions these models are designed to answer, hence motivating marketing researchers working in these and analogous areas to add this analytical tool to their statistical repertoire. We then present the models and show their relationships to a number of familiar models, beginning with regression. We want this chapter to be useful, even to the novice, so we work through a small illustrative data set, and we offer appendices with instructions on how to fit the models via two software packages. To illustrate the substantive insights that these models proffer, we also analyze a larger data set, reporting findings as one would do for a journal article. We close the chapter by returning to the varieties of marketing research questions that are well suited for these techniques.

### Motivation: Research Questions Suited for HLM

Figure 7.1 depicts a hierarchical structure of data. In the HLM jargon, there are micro units nested in macro units. In marketing, we might study customers as the micro unit, classified into segments defined by brand preference as the macro unit. In such a marketing application, we might interview customers and ask them which car manufacturer built the car they drive most frequently on a weekly basis, and we would form mutually exclusive and collectively exhaus-

Figure 7.1 **The Multilevel, Nested Structure Required of Data for Hierarchical Linear Models**

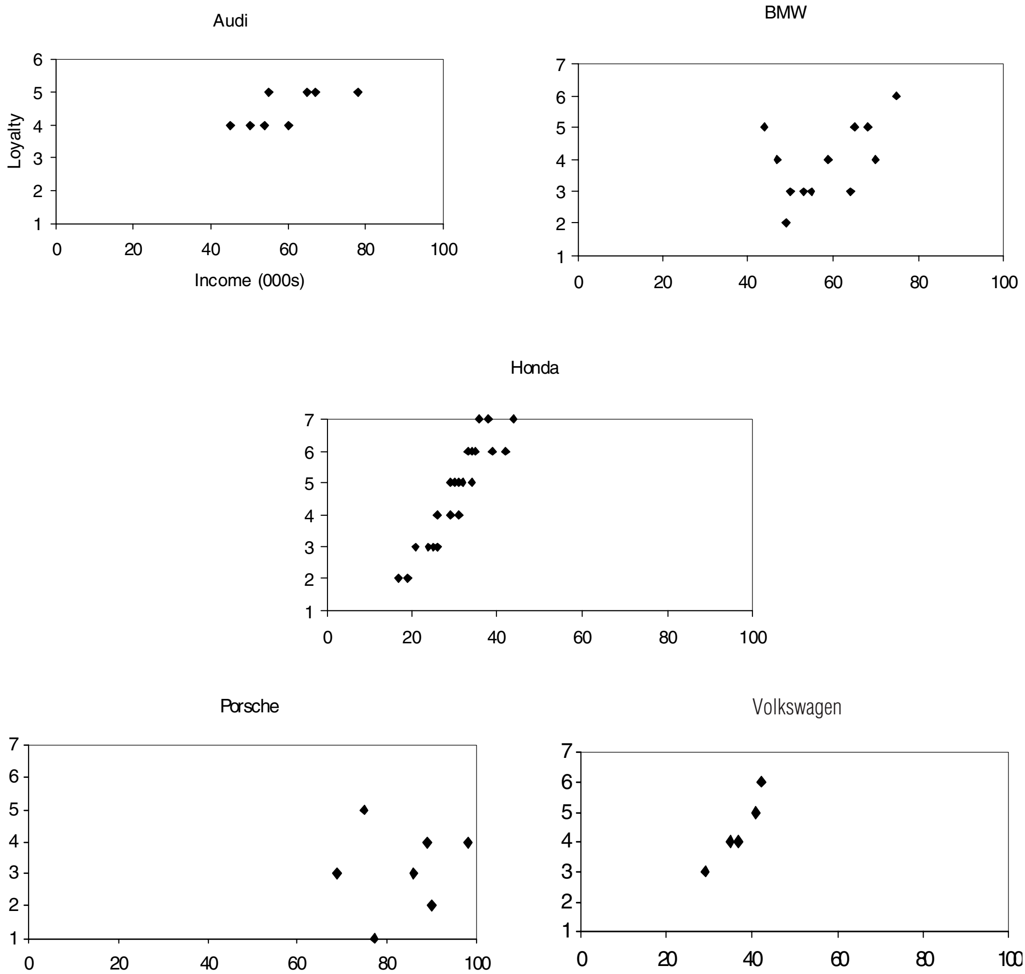



tive segments of drivers and their respective car makes. The numbers of customers nested in each car segment would presumably follow the car brand shares. Some brand choices are naturally exclusive (e.g., the bank that carries a household's main mortgage, the phone company that provides a household's local phone service). When brand choices reflect inherent variety seeking, customers still can be nested, depending on the question asked; for example, which brand of toothpaste is in your bathroom *today?*, which cereal do your children *like the most?*, on which airline frequent flier program do you have *the most miles?* Later, we will return to this assumption of the customers belonging to one and only one segment, but for now we assume this exclusive and exhaustive property.

An important line of statistical development on the HLM models was derived in the realm of education, wherein students are the micro units, attend one and only one school, and hence are nested in the school as the macro unit (Heck and Thomas, 2000; Luke, 2004; Raudenbush and Bryk, 2002). Analogously, HLM research conducted by organizational management researchers studies employees nested in firms (Hofmann and Stetzer, 1996; Seibert, Silver, and Randolph, 2004).

The multilevel context of hierarchical linear models raises a number of research questions. There might be basic comparisons across the macro unit brands; for example, which brand engenders the strongest preferences and claims of loyalty? HLM models can answer such questions, though questions of this simple nature might also be answered with mean comparisons. HLM is best suited for use on the nested structures as depicted in Figure 7.1. The model is intended for a micro level construct, being predicted by micro level and macro level constructs, where the nesting is taken into account. If a micro level dependent variable, such as "How likely is it you would buy this brand again for your next car?" is predicted only with other micro level predictor variables, say, household income, age and gender of driver, without considering the nested structure, a regular ordinary least squares regression could be run. But an interesting question that HLM allows answering is whether the relationships between those demographic variables and the dependent variable of repeat purchasing vary by brand. One could imagine sorting the data by brand, and conducting one regression per brand, but the resulting surfeit of models would be inelegant and not as powerful as using all the data simultaneously, nor would they allow for accurate comparisons across brands. In addition, HLM could incorporate macro level predictors, such as various consumer report qualities rated for each car make, or known attributes and features of the car (e.g., miles per gallon, 0 to 60 acceleration speeds), along with the micro level variables, to enhance the prediction and understanding of the micro/consumer level statements of loyalty.

Figure 7.2 **The Relationship Between Income and Loyalty, per Car Brand**




To help make this discussion more concrete, let’s work with a small data set. In Table 7.1, we present data that describe consumers’ stated intentions for anticipated brand loyalty to their cars (1 to 7, 7 = “I will definitely buy another [current car brand] for my next car”), which we will model simply as a function of their reported household income, for five car makes: Audis, BMWs, Hondas, Porsches, and VWs. (There is also a “macro” variable, the prestige rating of the car makes, which, as a macro variable, by definition does not vary within a car, and we will incorporate it also into the modeling later.) To offer a basic understanding of these data, Table 7.2 contains simple descriptive statistics: segment or brand group sizes, and the means on the loyalty rating and income variable. The car brand segments are significantly different on income ($F_{4,52}$ = 67.08, $p$<.0001) but not quite so on loyalty ($F_{4,52}$ = 2.11, $p$ = .0923).

In terms of the relationship between these variables, Table 7.3 contains the simple regressions, one model run per car, and Figure 7.2 contains the plots of these data. If a single regression were run on these data disregarding current auto ownership, the overall regression suggests no rela-

Table 7.1

**Illustration Macro and Micro Data**

| Car make (*j*) | $W_j$ = prestige of car | Consumer, *i(j)* | $Y_i$ = intended loyalty | $X_i$ = income ($000s) |
|---|---|---|---|---|
| 1 = Audi | 4 | 1 | 4 | 60 |
| 1 = Audi | 4 | 2 | 4 | 45 |
| 1 = Audi | 4 | 3 | 5 | 78 |
| 1 = Audi | 4 | 4 | 5 | 67 |
| 1 = Audi | 4 | 5 | 5 | 65 |
| 1 = Audi | 4 | 6 | 4 | 54 |
| 1 = Audi | 4 | 7 | 5 | 55 |
| 1 = Audi | 4 | 8 | 4 | 50 |
| 2 = BMW | 4 | 1 | 5 | 44 |
| 2 = BMW | 4 | 2 | 4 | 47 |
| 2 = BMW | 4 | 3 | 4 | 59 |
| 2 = BMW | 4 | 4 | 3 | 50 |
| 2 = BMW | 4 | 5 | 6 | 75 |
| 2 = BMW | 4 | 6 | 5 | 68 |
| 2 = BMW | 4 | 7 | 3 | 55 |
| 2 = BMW | 4 | 8 | 2 | 49 |
| 2 = BMW | 4 | 9 | 4 | 70 |
| 2 = BMW | 4 | 10 | 5 | 65 |
| 2 = BMW | 4 | 11 | 3 | 53 |
| 2 = BMW | 4 | 12 | 3 | 64 |
| 3 = Honda | 2 | 1 | 6 | 42 |
| 3 = Honda | 2 | 2 | 7 | 38 |
| 3 = Honda | 2 | 3 | 6 | 35 |
| 3 = Honda | 2 | 4 | 6 | 34 |
| 3 = Honda | 2 | 5 | 5 | 29 |
| 3 = Honda | 2 | 6 | 7 | 36 |
| 3 = Honda | 2 | 7 | 4 | 29 |
| 3 = Honda | 2 | 8 | 6 | 33 |
| 3 = Honda | 2 | 9 | 5 | 32 |
| 3 = Honda | 2 | 10 | 5 | 30 |
| 3 = Honda | 2 | 11 | 7 | 44 |
| 3 = Honda | 2 | 12 | 4 | 31 |
| 3 = Honda | 2 | 13 | 3 | 26 |
| 3 = Honda | 2 | 14 | 3 | 21 |
| 3 = Honda | 2 | 15 | 5 | 31 |
| 3 = Honda | 2 | 16 | 3 | 26 |
| 3 = Honda | 2 | 17 | 2 | 19 |
| 3 = Honda | 2 | 18 | 6 | 39 |
| 3 = Honda | 2 | 19 | 3 | 25 |
| 3 = Honda | 2 | 20 | 3 | 24 |
| 3 = Honda | 2 | 21 | 2 | 17 |
| 3 = Honda | 2 | 22 | 4 | 26 |
| 3 = Honda | 2 | 23 | 5 | 32 |
| 3 = Honda | 2 | 24 | 5 | 34 |
| 4 = Porsche | 5 | 1 | 4 | 98 |
| 4 = Porsche | 5 | 2 | 5 | 75 |
| 4 = Porsche | 5 | 3 | 3 | 69 |
| 4 = Porsche | 5 | 4 | 1 | 77 |
| 4 = Porsche | 5 | 5 | 2 | 90 |
| 4 = Porsche | 5 | 6 | 4 | 89 |
| 4 = Porsche | 5 | 7 | 3 | 86 |
| 5 = VW | 2 | 1 | 3 | 29 |
| 5 = VW | 2 | 2 | 4 | 35 |
| 5 = VW | 2 | 3 | 6 | 42 |
| 5 = VW | 2 | 4 | 5 | 41 |
| 5 = VW | 2 | 5 | 3 | 29 |
| 5 = VW | 2 | 6 | 4 | 37 |

Table 7.2

**Basic Descriptive Statistics**

| Brand | $\bar{x}$ income | $\bar{y}$ loyalty | $n$ |
|---|---|---|---|
| Audi | 59.25 | 4.50 | 8 |
| BMW | 58.25 | 3.92 | 12 |
| Honda | 30.54 | 4.67 | 24 |
| Porsche | 83.43 | 3.14 | 7 |
| VW | 35.50 | 4.17 | 6 |
| Total | 47.42 | 4.25 | 57 |

Table 7.3

**Ordinary Least Squares Regressions Results, One Regression per Car Make Predicting Loyalty (y) as a Function of Income (x)**

| Brand | R-squared | $\hat{\beta}$ | $p$-value |
|---|---|---|---|
| Audi | .50 | .71 | .0489 |
| BMW | .26 | .51 | .0932 |
| Honda | .86 | .93 | .0001 |
| Porsche | .01 | .12 | .8023 |
| VW | .91 | .95 | .0031 |
| Total | .00 | –.07 | .6275 |

tionship between income and loyalty (see the row labeled "Total" in the table). When a regression is run per brand, we see the picture more clearly as being contingent on car ownership. The loyalty of Honda, VW, and Audi owners is driven by income. The relationship is weaker for BMW drivers, and nonexistent for Porsche owners. These results are not unreasonable. Honda, VW, and Audi owners might appreciate value and reliability, whereas Porsche drivers may exercise their greater financial access to sample different car makes. With only a few cars, Table 7.3 is fairly succinct. Note, however, that our summary has been qualitative, and to make comparisons properly, we would need to conduct the statistical tests comparing the betas for the different car owners. HLM will yield results that contain all this information, and more, and do so more parsimoniously, more powerfully, and more properly. After presenting the HLM models, we will return to these data to discover what insights the HLM technique offers.

Before doing so, however, we wish to emphasize that the statistical modeling approach of HLM is applicable to many more marketing questions beyond studies of customers and brands, central as those questions might be to marketing. The basic requirement of HLM is that there exist micro level data that are to be modeled as a function of micro and/or macro level data. There are a myriad of micro/macro questions in the marketing literature. Following are several examples.

Previous research in marketing utilizing HLM includes studying the effects of accountability on advertising managers' reactions to a series of advertisements (Brown, 1999), analyzing the conjoint ratings of key informants within multiple distribution channels (Wuyts, Stremersch, Van den Bulte, and Franses, 2004), understanding diffusion patterns through incorporation of economic growth patterns (Van den Bulte, 2000) and social contagion effects (Van den Bulte and Stremersch, 2004), and understanding the effects of satisfaction with specific aspects of an organization's product or service on overall customer satisfaction across subunits of an organization (Malthouse, Oakley, Calder, and Iacobucci, 2004). HLM is used to model longitudinal data by Brown (1999) and Wuyts et al. (2004) where the individual responses over repeated measures act as the micro level parameters and the managers fill the macro level role. The research by Van den Bulte (2000) and Van den Bulte and Stremersch (2004) looks at diffusion rates, using products as the micro parameters, with macroeconomic and social contagion effects operating as macro variables. Malthouse et al. (2004) look at customer satisfaction, modeling satisfaction with various aspects of the product or service at the micro level, and utilizing organizational subunits in the macro role. Note that these questions do not involve simple mean comparisons; rather, they involve comparing macro units in an assessment of the strengths of relationships among micro and macro variables. These marketing questions and many more may be addressed using HLM models. We will provide additional details on each of these studies, as well as a discussion of other relevant questions for marketing researchers, at the end of this chapter. We now turn to the models.

## Introduction to HLM Terminology and Notation

A question that seems inevitable is: "Why do we have to learn a new technique to answer these research questions?" Researchers have posed questions of these sorts for decades, and surely they have been analyzing their data to extract answers. They have. But not surprisingly, we will show that the previous approaches are suboptimal compared to HLM. Let's take a look at the simpler alternatives.

### *An Old Way: Aggregating*

In the context of our branding questions, wherein the micro units are customers and the macro units are the brands to which they profess allegiance, we might try to run an ordinary least squares (i.e., "regular OLS") regression, but we would quickly encounter the question of how to incorporate the fact that the data are measured at different levels. We would have to choose a common level. We could either aggregate the micro level up to the macro level and work at the macro/brand level, or we could choose to model the micro level and disaggregate the macro data down to the micro level. For the first approach, we would take the simple means of income and of loyalty within each of the car brands, which would result in a single $\bar{x}$ and a single $\bar{y}$ for each brand. The choice in units of observation changes our effective sample sizes: Instead of $n = 57$ car owners, we would be analyzing a data set in which $n = 5$ car brands.

Clearly, the aggregation may be criticized. First, given the fact that this illustrative data set is so small, that is, has so few macro units, we would be hard-pressed to run a regression on the five macro level data points. Although five might be excessively small, we would face this philosophical difficulty of aggregation even if the number of macro units were 10 or 20. Some secondary databases exist which are not so limited in this manner (e.g., the scanner panel types of data referred to previously), but much of survey or experimental lab data may not yield a substantial number of macro units.

Aggregation is also frequently criticized as "throwing away information." The income and loyalty data vary across customers within each car make, and that within group variance is interesting; for example, the 24 different incomes and loyalty perceptions of the 24 Honda owners are now represented by a single mean for each variable. This within macro variability is obliterated when a single mean score is used to represent all micro units within the macro group.

A by-product of aggregation is that the mean income and mean loyalty data are more "reliable" as data points than any single score (at the micro or macro units). Reliability is usually encouraged as a good thing, but here that assessment is not so straightforward. First, the Honda segment is larger than the Porsche segment, for example, so the Honda data will be differentially more reliable than the Porsche data. Any exercise in seeking brand differences will be more powerful for the Honda group compared with the data for Porsche. Second, if the micro data were aggregated, they would be more reliable (being means), so if they were included in a model with the macro data points, the (more reliable) micro data would likely swamp the effects of the macro data. In some sense, none of these effects are "real"; rather, they would be statistical artifacts, albeit predictable ones.

### *An Old Way: Disaggregating*

The alternative of disaggregation was also posed. The macro level variable would simply be replicated for each micro unit, much as it appears in Table 7.1. The problem is that the Honda prestige score of "2" for Honda customer 1 is the same data point and not unique from the Honda prestige score for customer 2. If we have a single piece of information and we replicate it once per person within each macro unit, we have created a data set that lacks statistical independence between observations, violating a fundamental assumption that is required of most general linear models. In essence, we have created a serious case of multicollinearity.

The general consensus is that, in this choice between aggregating and disaggregating, the former is better (cf. Raudenbush and Bryk, 2002). When working at the aggregated macro level, you give up data points, but that is statistically superior to creating purported new data that lack independence in the disaggregate micro level analyses.

The mix of micro and macro data is so pervasive, and the shortcomings of the aggregation and disaggregation approaches so clear, that researchers have certainly tried even more alternatives. Previously, we alluded to the possibility of fitting a regression model within each macro unit. When the macro units, in this case brands, are randomly sampled from their population, the model is referred to as a "random effects" or "variance component model." This approach yields one slope parameter that is constant across all brands, with different intercept terms, one per brand. Next, those resulting beta estimates could be modeled as a function of the car brand's prestige scores. In essence, this is the logic of HLM, but the HLM technique is superior given that the micro and macro modeling is conducted simultaneously.

To fit the model in pieces, that is, not via HLM, would be an approach we could characterize as inelegant. Alternatively, we might fit a "random coefficients regressions," in which both slopes and intercepts would depend upon brand. This approach is an improvement, but it still does not allow for the incorporation of the macro level variables, for example. We will return to alternatives such as these later in the chapter. For the moment, we hope we have persuaded the reader that multilevel, hierarchical data might occur frequently in marketing and that we need to address the substantive questions using appropriate statistical tools. Hence, we now present the basics of the HLM modeling approach.

## The Hierarchical Linear Model

Hierarchical linear models are alternatively (in different literatures) called, or related to: multilevel linear models, mixed effects models, random effects models, random coefficient regression models, or covariance components models (cf. Achen and Shively, 1995; Berry, Levinsohn, and Pakes, 1995, 2004; Bock, 1989; Raudenbush and Bryk, 2002; Goldstein, 1995; Heck and Thomas, 2000; Kreft, 1995; Kreft and Leeuw, 1998; Nevo, 2000, 2001; Raudenbush and Willms, 1991). We will be very careful with these labels, which are sometimes used interchangeably or imprecisely. It is important to simply look at the model statements themselves. We will, however, use the terms *HLM* and *multilevel models* interchangeably.

HLM or multilevel models are useful for three statistical reasons and two substantive ones. First, the statistical reasons. Perhaps of primary importance is simply the fact that the HLM models capture the inherent structure in the data. To aggregate up or disaggregate down requires assumptions that do not represent the data, and doing so inevitably introduces error and bias. A second, related point is that HLM models avoid the problematic estimation that results from disaggregation (treating the micro data within the macro unit as if they were independent) and the Type I errors that result from standard errors being "too small" when choosing the aggregation path (recall the previous discussion that the means are more, i.e., "too," reliable; cf. Raudenbush and Willms 1991). Third, HLM models can help the researcher struggling with issues of statistical power. That is, one advantage of fitting the micro and macro models simultaneously is that there is greater sensitivity to detect significant relationships. Given the nature of the data, there are always fewer macro units than micro, and if the macro units are indeed sparse in number, the models give a "boost" to the macro level modeling (Heck and Thomas, 2000). Alternatively, and for analogous reasons, some macro units may contain few micro units (e.g., brands with small shares), which on their own might obviate the possibility of stable regression estimates. Once again, the simultaneous fitting and estimation in HLM enhances the entire data set and modeling exercise. The number of nested, hierarchical levels would not be limited by the modeling but only by the data requirements (i.e., the difficulty in obtaining "reasonable" sample sizes at micro, macro, macro-macro, etc., levels, where "reasonable" would be defined to reflect the essential nature of HLM models that a regression is fit at each level).

There are two substantive reasons that HLM models dominate others we have discussed. First, it would not be unusual for a researcher to have hypotheses at both the micro and macro levels, and thus empirically there is a curiosity about the entire data set, not just parts of it modeled suboptimally (cf. Rousseau, 1985). A second scenario in which HLM models can be useful is that they allow for the representation of cross-level interactions–that is, an effect that is contingent between a micro and macro variable, as for example, "Is there a synergy between the prestige (macro) of a car and a consumer's (micro) income level, beyond whatever main effects exist for either?".

We have presented some of the reasons for conducting HLM models. Let's now see them in action.

### *The Fundamental Micro Level Regression*

Starting with the basics, imagine a single micro level, familiar regression model, seeking to test whether there is a relationship between income ($X$) and loyalty ($Y$) for one car brand:

$$Y_i = \beta_0 + \beta_1 X_i + e_i. \quad (1)$$

The error term, $e_i$, has the usual ordinary least squares assumptions (i.e., independence of observations, and normal errors, $N(0, \sigma^2)$ for subsequent hypothesis testing). The notation posits a model of consumer $i$'s stated loyalty ($Y_i$) as a function of $i$'s income ($X_i$), all within a single macro unit (brand). (Note that a familiar notation for nesting would be $X_{i(j)}$, however, this notation is not prevalent in the HLM literature.)

If we fit this model to only the Audi data in Table 7.1 (and then in turn to the other cars' data), we will obtain an estimate for each beta (per Table 7.3). There are few data and fewer parameters; furthermore, the models have not gotten complex yet, so it is easy to keep track of the parameters thus far. However, the models will become increasingly complicated, and it helps to attach conceptual labels to both the intercept and slope. In this context, the intercept captures a level of baseline loyalty, or the expected level of loyalty when income is zero. The slope parameter reflects the extent to which income explains acclaimed loyalty. Strong, positive $\beta_1$ estimates would indicate that households with greater incomes were more brand loyal, whereas strong, negative

$\beta_1$s would reflect greater loyalty among households with lesser incomes, perhaps reflecting households seeking reliability and value for their relatively limited budget.

### *The Micro, Level 1 Model*

Let's introduce the first level of added complexity. For the full micro, or "Level 1" model of HLM, we will simultaneously model all the brands, not just the data for Audi. Now we have $J$ car brands ($j$ = 1, 2, . . . $J$), and we extend the models to include all of the brands, the $j$'s, and the customers loyal to (within) each brand, the $i$'s:[1]

$$(2) \qquad Y_{ij} = \beta_{0j} + \beta_{1j}(X_{ij} - \bar{x}_j) + e_{ij}.$$

$Y_{ij}$ is the stated loyalty intentions of consumer $i$ for car $j$. $X_{ij}$ is income, and $\bar{x}_j$ is the mean income across consumers within car $j$. (There is a bit of debate in the HLM literature about this mean centering,[2] but in truth, it only slightly affects the interpretation of $\beta_{1j}$. If the model contains only $X_{ij}$, then a positive $\beta_{ij}$ means that loyalty rises as income rises, whereas if the model statement contains $(X_{ij} - \bar{x}_j)$, then for a positive $\beta_{1j}$, we would say that loyalty rises as income rises, relative to the mean income.)

Equation (2) indicates that we will obtain one estimate of the intercept, $\beta_{0j}$, and one estimate of the slope $\beta_{1j}$, for each car brand $j$. In HLM, once we have estimated this two-vector piece of information on each of the brands (i.e., the pairs of $\hat{\beta}_{0j}$ and $\hat{\beta}_{1j}$), the question is, can we predict and understand these coefficients using whatever other information and data we might have on the macro units (the brands)?

### *The Macro, Level 2 Model*

To restate the question, we seek whether, at the macro level, we can model the micro level beta estimates (both intercepts and slopes) as a function of any macro level information, that is, the $W$ variables:

(3) *Modeling the intercepts:* $\beta_{0j} = \gamma_{00} + \gamma_{01} W_j + u_{oj}$.
(4) *Modeling the slopes:* $\beta_{1j} = \gamma_{10} + \gamma_{11} W_j + u_{1j}$.

Note that similarly to models (1) and (2), wherein we include only a single micro level predictor, $X$, for the moment, we keep the macro level models simple as well, with just a single $W$ for now. The notation is a little weird, but models (3) and (4) are just regressions, having the analogous form to the regression model in (2) Instead of betas on the right-hand side of the equation, we have gammas, but the first gamma in (3) and in (4) is an intercept: $\gamma_{00}$ is the intercept for modeling $\beta_{0j}$, which in turn were the intercepts in model (2), that is, the terms capturing overall brand loyalty; and $\gamma_{10}$ is the intercept for $\beta_{1j}$, the effect of income on loyalty in model (2). The second set of gammas are the slopes that reflect whether the overall brand loyalty $\beta_{0j}$ is a function of $W$ or not (i.e., $\gamma_{01}$) and whether the income effect, $\beta_{1j}$ may be explained by car prestige $W$ or not, $\gamma_{11}$. The final terms, $u_{0j}$ and $u_{1j}$,are error terms.

In the next step, we simply perform an algebraic substitution. We insert the macro equations, (3) and (4), into the micro model (2):

$$(5a) \qquad Y_{ij} = (\gamma_{00} + \gamma_{01} W_j + u_{oj}) + (\gamma_{10} + \gamma_{11} W_j + u_{ij})(X_{ij} - \bar{x}_j) + e_{ij},$$

multiply through:

$$(5b) \qquad Y_{ij} = \gamma_{00} + \gamma_{01} W_j + u_{0j} + \gamma_{10} (X_{ij} - \bar{x}_j) + \gamma_{11} W_j (X_{ij} - \bar{x}_j) + u_{1j} (X_{ij} - \bar{x}_j) + e_{ij},$$

and collect terms:

$$(5c) \qquad Y_{ij} = \gamma_{00} + \gamma_{01} W_j + \gamma 10 (X_{ij} - \bar{x}_j) + \gamma_{11} W_j (X_{ij} - \bar{x}_j) + u_{0j} + u_{1j} (X_{ij} - \bar{x}_j) + e_{ij}.$$

Equation (5c) is the basic HLM model (Raudenbush and Bryk, 2002; Heck and Thomas, 2000), with a single micro predictor, *X,* and a single macro level predictor, *W.* Let's pull (5c) apart and examine what the pieces mean.

First, note that given the complexity of equation (5c), running an ordinary regression is no longer suitable. There are three error terms, the micro $e_{ij}$, the macro $u_{0j}$, and a rather complex-looking interaction between a macro level error term and the micro level predictor, $u_{1j}(X_{ij} - \bar{x}_j)$. If we ran a regular regression rather than HLM, these effects would not be partitioned, and the tests of whether the micro and macro effects were significant would be contaminated. Just as in regular OLS regressions, in which we do not usually report the error terms (although we often mention their obverse, variance accounted for, *R*-squared), here too, there is little interest in the error terms, $e_{ij}$, $u_{0j}$, *and* $u_{1j}$, except as diagnostics: the level 1 error, $e_{ij}$, captures the heterogeneity across customers within the same car brand, and therefore merely reflects "within-group" variability or individual differences. If our model should indicate that the variance component for $u_{0j}$ is significant, then the brand means differ, and therefore it is worth investigating and modeling them, that is, per model (3) or (5c). Analogously, if the variance component for $u_{1j}$ is significant, then the brand slopes differ, meaning that the strength of the relationship between the micro dependent variable (i.e., loyalty) and the micro predictor (i.e., income) varies across the brands, and therefore would be interesting to pursue in the modeling.

Here is a listing of the interpretation of the model terms:

- The different $u_{0j}$ 's reflect variability across the brands in overall brand loyalty means.
- The different $u_{1j}$ 's reflect variability across the brands in terms of the slopes, which in turn reflect the strengths of the relationships between income and brand loyalty.
- If $\gamma_{00}$ is significant, it means that the overall brand loyalty mean is significantly different from zero.
- A significant $\gamma_{01}$ indicates that the macro variable "prestige" helps explain the overall brand loyalty means (e.g., if the coefficient is positive, then as prestige increases, the brand mean is greater).
- A significant $\gamma_{10}$ would indicate that overall, the brand slopes are nonzero, that is, there are significant relationships between the income and loyalty measures.
- Finally, a significant $\gamma_{11}$ indicates that the macro variable "prestige" helps explain the brand slope differences; for example, if it is positive, then as the prestige of the car increases, the strength of the linear relationship between income and loyalty increases (or, the more prestigious cars show the strongest relationships between income and loyalty).

With that basic template in mind, let's return to the car brand data.

## The Car Brand Data Analyzed via HLM

We fit the full HLM model to the data in Table 7.1 (see Appendix 7.1 for SAS syntax and Appendix 7.2 for the HLM software syntax). Recall the model:

$$(5c) \qquad Y_{ij} = \gamma_{00} + \gamma_{01}W_j + \gamma_{10}(X_{ij} - \bar{x}_j) + \gamma_{11}W_j(X_{ij} - \bar{x}_j) + u_{0j} + u_{1j}(X_{ij} - \bar{x}_j) + e_{ij}$$

Given the preceding template for interpreting the substantive parameters, we have the following results: $\hat{\gamma}_{00} = 10.18$, $t = 7.62$, $p < .005$, leading to the conclusion that there is an overall brand loyalty effect (i.e., the brand loyalty baseline is substantially greater than zero).

The estimate $\hat{\gamma}_{01} = -1.56$ is also significant ($t = -4.02$, $p < .0001$), indicating that the macro variable of prestige carries a main effect in discerning the brands' loyalty differences. Specifically, the sign of the parameter is negative, so this main effect suggests that cars with greater prestige tend to elicit less driver loyalty.

The third regression weight in (5c) is also significant, $\hat{\gamma}_{10} = .32$, $t = 7.97$, $p = .0001$. This parameter indicates that the brands' slopes are significant. The slopes of course reflect the strengths of relationship between the loyalty dependent variable and income which differs across the brands. The positive sign indicates that, separate from a car's prestige (the $W$ main effect of $\hat{\gamma}_{01}$), the main effect of $X$ is such that households with greater incomes tend to show greater loyalties.

Finally, the significant estimate $\hat{\gamma}_{11} = -.06$ ($t = -5.96$, $p < .0001$) indicates an interactive contingency that those significantly different brand slopes may be explained in part by the macro variable prestige. Again, note the negative sign on the estimator, and we would conclude that for the cars with greater prestige, the linear relationship between income and loyalty is weakened. In the case of car brands with less prestige, income drives loyalty. For the more prestigious cars, income is less predictive of loyalty.

The simple descriptive statistics on the car brand data earlier foreshadowed some of these findings, but lacked both power and parsimony, and finally did not address all the research questions we have now answered. This illustrative exercise was small scale, so the interested reader might take his or her hand at replicating the results. We now turn to a larger data set.

### A Larger, Real-World Illustration

In this larger scale, real-world data set, we examine 101 media organizations representing a stratified random sample of the U.S. media industry (see Malthouse et al., 2004 for details on the sampling method). Together these 101 firms employ a total of over 31,000 people. HLM models are well suited to capture the inherently hierarchical nested nature of the 31,000 employees within their respective organizations. Our data contains survey responses from a purposive sample of 5500 of these employees. Whereas previous studies using these data have focused on modeling customer outcomes (Calder and Malthouse, 2003; Malthouse et al., 2004), in our modeling for this chapter, we focus on data from the employees. These actors—customers and employees—are thought to be interrelated, of course, through the concept of a firm's customer orientation. Thus, before proceeding to the data analysis, we briefly describe the theoretical nature of the conceptual relationships we seek to test.

Although data obtained from employees in organizations are often modeled to understand organizational management concepts, our aim in this chapter is to provide a clear example in a marketing context. Accordingly, we will use an organization's "customer orientation" as our dependent variable. The origin of the customer orientation construct dates back to early research on the implementation of the marketing concept (Kohli and Jaworski, 1990; Narver and Slater, 1990), and was solidified as a measurable construct in the work of Deshpandé, Farley, and Webster (1993) and as a component of the Narver and Slater (1990) model of market orientation (along with competitor orientation and interdepartmental coordination) An individual employee's perception of the customer orientation of the organization provides a good barometer of the extent to which an organization has built itself around providing products or services designed with the customers' best interests in mind (Deshpandé et al., 1993) As such, studying customer orientation as our dependent variables offers a relevant and useful context for describing an empirical example of HLM in marketing.

Researchers have identified a number of factors that might potentially affect an organization's level of customer orientation, including market competitiveness (Jaworski, 1988; Slater and Narver, 1994), organization size (Jaworski, 1988), and managerial practices and behavior (Jaworski and Kohli, 1993; Kohli, 1985; Lee and Miller, 1999; Mohr-Jackson, 1992) We have incorporated each of these factors in our study. Table 7.4 depicts the mapping of these constructs to the following variables in our study:[3] level of competition, number of employees, employee perceptions of role clarity, employee involvement, and communication of organizational mission. We also included data on employee perceptions of product quality to gauge whether they are more likely to evaluate their organization as more customer oriented if they also believe the organization offers high-quality products.

As pertaining to this chapter, these data exist at different levels. The data representing employee perceptions comprise our micro level (Level 1) data. The data representing variables associated with the organization as a whole (e.g., total number of employees, level of competition) can be collected as a single measure for the entire organization, and hence serve as our macro level (Level 2) data. HLM offers the opportunity to analyze these data using both the organizational level and the individual employee level data.

We will model customer orientation as a function of the four micro level (Level 1) variables (i.e., role clarity, employee involvement, communication of mission, and product quality) and two macro level (Level 2) variables (level of competition and total number of employees). For purposes of simplification, we used a subset of the larger data set, randomly sampling 14 organizations represented by 6181 individual employees. This organizational sample contains data from 871 of the surveyed employees. Table 7.5 provides descriptive statistics for each of these variables.

Our theoretical predictions are briefly these: we expect to see role clarity, employee involvement, communication of mission, and product quality all to have a positive influence on perceptions of customer orientation. In contrast, we expect increasing levels of competition to alter the organizational focus from a customer orientation to a competitor orientation (a component of the Narver and Slater, 1990, model of market orientation). Similarly, we expect larger organizations would struggle to effectively implement a customer orientation. Thus, competition and size of firm should yield negative effects.

Now, on to the results of our HLM analysis. In addition to testing for the fixed effects on the dependent variable of customer orientation of each independent variables (the four micro and two macro variables), we also test for cross-level interactions, that is, do the macro level variables moderate the effects of the micro variables on the dependent variable?

Table 7.6 contains the parameter estimates from the model. The results show that three of the four micro level indicators and one of the two macro level indicators are significant predictors of our dependent variable, customer orientation. At the micro level, employee perceptions of product quality, employee involvement, and communication of the organizational mission all positively influence the employee's perception of the organization's level of customer orientation, per our hypotheses. At the macro level, we see that increased levels of competition do indeed reduce the perceived level of customer orientation, as we had predicted. Note that at the micro level, role clarity by itself does not significantly influence perceived customer orientation, nor does the size of the organization, a macro variable, significantly contribute to the model as a main effect.

Table 7.4

**Operationalization of Independent and Dependent Variable Constructs**

| Variable | Construct definition | Level | # Measures | Reliability |
|---|---|---|---|---|
| Dependent variable | | | | |
| Customer orientation | Employee perceptions of customer orientation | Micro | 5 | $\alpha$ = .77 |
| Independent variables | | | | |
| Competition | Level of market competitiveness | Macro | 1 | |
| Number of employees | Organization size | Macro | 1 | |
| Managerial practices and behavior | | | | |
| Role clarity | Employee perceptions of role clarity | Micro | 3 | $\alpha$ = .76 |
| Employee involvement | Employee perception of involvement | Micro | 4 | $\alpha$ = .77 |
| Mission communication | Communication of organizational mission | Micro | 5 | $\alpha$ = .78 |
| Product quality | Employee perceptions of product quality | Micro | 6 | a = .80 |

Table 7.5

**Descriptive Statistics: Means, Standard Deviations, and Correlations**

| Variable | i or j | Construct | Mean | SD | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Micro (i) | Customer orientation[a] | 3.59 | 0.90 | 0.77 | | | | | | |
| 2 | Micro (i) | Product quality[a] | 3.76 | 0.82 | 0.49 | 0.80 | | | | | |
| 3 | Micro (i) | Role clarity[a] | 4.21 | 0.78 | 0.37 | 0.46 | 0.77 | | | | |
| 4 | Micro (i) | Employee involvement[a] | 3.50 | 1.08 | 0.43 | 0.55 | 0.40 | 0.77 | | | |
| 5 | Micro (i) | Mission communication[a] | 3.64 | 0.94 | 0.43 | 0.57 | 0.51 | 0.63 | 0.78 | | |
| 6 | Macro (j) | Competition[b] | 1.80 | 0.78 | –0.05 | –0.14 | –0.06 | –0.01 | –0.07 | NA | |
| 7 | Macro (j) | Number of employees[c] | 639.18 | 410.46 | 0.03 | 0.18 | 0.07 | 0.09 | 0.16 | 0.06 | NA |

*Note:* Coefficient alpha (scale reliability) represented on diagonal where applicable.
[a]Measured with 1–5 scale, where 5 represents positive response.
[b]Measured on *ln*(1–25) scale.
[c]Number of employees ranged from minimum of 53 to maximum of 1,199.

Table 7.6

**HLM Coefficient Estimates—Customer Orientation as Dependent Variable**

| | Hypothesis | Estimate | Standard error |
|---|---|---|---|
| Product quality (i) | + | 0.3369* | 0.080 |
| Role clarity (i) | + | –0.0909 | 0.103 |
| Employee involvement (i) | + | 0.2377* | 0.067 |
| Mission communication (i) | + | 0.1685* | 0.079 |
| Competition (j) | – | –0.3476* | 0.181 |
| Number of employees (j) | – | 0.0003 | 0.000 |
| Employee involvement x number of employees (ixj) | | –0.0002* | 0.000 |
| Role clarity x competition (ixj) | | 0.0964* | 0.040 |

*$p \leq 0.05$
(i) Micro-level variable
(j) Macro-level variable

What is interesting and important to note, however, is the ability of these two indicators, which are not significant as main effects, to find their way into the picture through their significant interactions with indicators at the other level, that is, the interaction between role clarity (micro) and competition (macro), and between employee involvement (micro) and number of employees (macro) Specifically, the positive parameter estimate for the role clarity by level of competition term suggests that either as the level of competition increases, the importance of role clarity also increases, or, as role clarity increases, the effect of competition is stronger. (Between these two explanations, the former is probably the more reasonable, but these models are still "correlational" and the causal direction must be informed by the theoretical context.) With regard to the negative parameter estimate for the interaction between firm size and employee involvement, it would appear that as the size of the organization increases, the organization's efforts at generating employee involvement are less effective. (Of course, the reverse causal direction is conceivable—that firms whose employees are not greatly involved are not likely to evolve to be large firms.)

Interpreting these results, we conclude that in order for employees to feel as if their organization is focused on the customer, employees need to feel that they are providing customers with a high-quality product or service. These employees must also feel that they are effectively involved in determining what they do to serve their customers, and they must feel that the organization's mission is well communicated throughout the organization. On the other hand, as organizations grow larger, employees respond that efforts at involving them in decision making fall short. Affecting all of this at the macro level, however, is the organization's level of competition. In a highly competitive environment, the employees perceive their organization as being less customer oriented, perhaps because of an increased focus on its competitors. In such a competitive environment, employees feel that their role in the organization must be clearly defined in order for them to execute a customer-oriented approach.

## Extensions and Limitations

The small illustrative data set we analyzed on car brand loyalty was an example of a simple regression with a single predictor at the micro level, one *X,* and a single predictor at the macro level, one *W.* The real-world data set on perceptions of customer orientation in organizations was already more complex, reflecting the real needs of researchers requiring more representative models with multiple $X$'s and $W$'s, and their interactive product terms. These generalizations are straightforward both in terms of the logic, that is, being no different from extending multiple regression from $\beta_1$, to $\beta_1, \beta_2, \ldots, \beta_k$ predictors, as well as in the syntax of the popular HLM software packages, wherein the analyst simply lists more $X$ and $W$ variables in the model statements (see Appendices 1 and 2).

There are certainly other extensions. In the next section, we return to some marketing applications and uses of HLM, and therein present some varieties including longitudinal data and meta-analyses. In longitudinal applications, the repeated measure usually serves as the micro level data point, and the source of the multiple measures (e.g., a household) serves as the macro unit. In meta analyses, the results of a given study in a particular article can serve as the micro unit, and the teams of scholars can serve as a macro unit, for example.

A natural question arises as to numbers of levels. The statistical theory and analytical logic is not limited to micro and macro-nits. Three or more levels can clearly be incorporated into a nested data set. Three or more levels is rarely seen, however, for two pragmatic reasons: first, such a scenario would require even more extensive data collection and matching by nested units. Second, the data analyses are further complicated by computing packages tailored for two levels. Three levels may currently be handled by the HLM software, and theoretically any number by SAS.

A related practical question may be posed about the number of units, or sample sizes, at both the micro and macro levels required to produce stable parameter estimates and model fit statistics. Limited guidance exists in this regard beyond common statistical sense; given the typical linearity of these models, and subsequent accompanying assumptions of normality, we know that the central limit theorem becomes relevant for $n > 30$; yet frequently (cf. Table 7.7), the number of macro units can fall short of this goal, as can the number of micro units therein nested.

Any methodological technique has limitations, and HLM is no different in this regard. The nested, multilevel structure is pervasive in many marketing domains, but it is not characteristic of others. Furthermore, even in a hierarchical domain, the HLM models posit a micro data point as the dependent variable. If the researcher is more interested in how the micro and macro variables interplay in their effects on other macro variables, HLM models are not applicable, and the researcher is best off aggregating the micro data up to the macro level and conducting all the modeling at that aggregated, macro level, albeit presumably on an effectively small sample.

A final natural question that arises frequently in marketing is how to treat data that are categorical (e.g., particularly dependent variables such as brand choice). Again, in theory these models are easily extended, and yet in practice, the accessible software is geared toward linear relationships among continuous measures. Developmental research could be conducted to create the extensions or to study the robustness of the application of improper linear techniques to the logistic regression setting.

We had cautioned early in the chapter that the clearest use of HLM is when a micro unit is nested in one and only one macro unit. This exclusivity has always been a characteristic in experimental designs, for example. This quality has also characterized some grouping algorithms such as hierarchical cluster analyses. Yet, like cluster models expanding to overlapping clusters, for which a consumer might be present in membership in multiple clusters or segments, perhaps probabilistically as in fuzzy clusters (Arabie and Hubert, 1994), it is easily conceivable that HLM distinctions of micro nesting in macro units might further be generalized and extended as well.

Finally, although HLM models are related to a number of other analytical techniques (see Appendix 7.3), the superiority of HLM over the classic methods has not been empirically demonstrated. Clearly, in certain situations that have inherent hierarchical nesting, theoretically the HLM approach should prove superior. Hence, simulation work would be useful to explore the conditions under which one technique would outperform another.

## Marketing Applications of HLM

Table 7.7 displays a number of recent marketing articles that incorporate a hierarchically-structured logic. We had briefly mentioned some of the representative applications in the marketing literature. At this point, we will provide more detail on each of those studies and their use of HLM.

Brown (1999) studied advertising managers' reactions to a series of ads, measuring their private evaluations of the ads, as well as their anticipation of publicly defending an assessment of the ads. She found that, in contrast to the predictions of the extant literature, the managers' public assessment would be more objective than their private ratings and that the managers modified their public judgments toward conciliation with those respective public constituencies. At first glance, this application may not seem to be one with a micro/macro character, but the study was conducted via a mixed experimental design, in which the multiple ad executions served as a repeated measures factor. Brown used HLM with ads as the micro units and the manager (each of whom rated each ad) as the macro unit. The manager's private ratings of those ads served as a stimulus/micro level covariate, which corrected for any response biases, and allowed the between-manager/macro comparisons to be cleaner, having statistically controlled for such extraneous individual differences. Analogously, Wuyts et al. (2004) collected conjoint ratings from key informants in multiple distribution channels, and to clarify the results of the conjoint foci (i.e., preferences, choices, and attributes), these researchers modeled the innate managerial preference heterogeneity via a set of micro level parameters. In Appendix 7.3, we say more about how an HLM approach compares with standard general linear modeling approaches to these questions.

The logic and methods of HLM have also been applied in meta analytical settings. The studies and basic findings serve as the micro unit of analysis, and the theoretically interesting comparative factors become the macro units. For example, in a study of new product diffusion rates, Van den Bulte (2000) treated products as micro units, so that different products could vary in their attractiveness rates in entering the marketplace. That is, he acknowledged that these rates could vary randomly, and beyond that variability, he incorporated model parameters to test explanations for the apparent increase in diffusion rates, such as the purchasing power of economic growth periods, or the converse, for example, unemployment. In subsequent research, Van den Bulte and Stremersch (2004) sought to tease apart the economic price and social contagion explanations for the variations in the diffusion rates. Using data from multiple countries and multiple products, they were able to demonstrate the importance of economic and network effects, and furthermore, tied these social operators to cross-cultural properties.

A number of business organizations are comprised of multiple subunits, whether we are talking about automotive manufacturers and their multitude of dealers or media conglomerates and their multiple holdings (e.g., newspapers, television stations, magazines). In their application of HLM, Malthouse et al. (2004) demonstrate that the drivers of customer satisfaction may vary across subunits of an organization and that the ability to distinguish such differences is eliminated when using conventional regression techniques. HLM allows for the incorporation of the subunit as a macro variable, allowing for the identification of differences across subunits of a single organization.

Table 7.7

**HLM Studies in Marketing**

| Study | Journal, year | Setting | Macro unit | # Macro units | e.g., Macro variable | Dependent variable | Statistical comment |
|---|---|---|---|---|---|---|---|
| Baumgartner and Steenkamp | JMR, 2001 | Survey responses | Country | 11(5) | Italy (acquiescence) | Response style bias | Three level HLM |
| Bell, Bonfrer, Chintagunta | JMR, 2004 | Product choice | Brand of toothpaste | 10 | Crest | Market share | Conditional logit |
| Bordley | JMR, 2003 | Automobile market | Car segment | 8 | Luxury | Profit | Flexible random coefficients logit |
| Brown | Mktg Sci, 1999 | Advertising managers | Manager | 62 | Manager judgment | Ad ratings | Repeated measures |
| Chintagunta | JMR, 2002 | Product choice | Brand | 5 | Tylenol | Sales | Flexible random coefficients logit |
| Malthouse et al. | JSR, 2004 | Customer satisfaction | Firm subunit | 3 (3) | | | |
| Oakley, Iacobucci, and Duhachek | Chapter, 2004 | Customer orientation | Organization | 14 | Level of competition | Customer orientation | HLM |
| Sudhir | Mktg Sci, 2001 | Product choice | Yogurt manufacturer | 2 | Dannon | Price | Logit |
| Sudhir | Mktg Sci, 2001 | Automobile pricing | Manufacturer (segment) | 4 (5) | GM, Ford | Price | Flexible random coefficients logit |
| Van den Bulte | Mktg Sci, 2000 | Product diffusion | Economic growth | 31 | Cellular phone | Diffusion speed | Single stage hierarchical model |
| Van den Bulte and Stremersch | JMR, 2004 | Product diffusion | Consumer durables (country) | 52 (28) | Television | q/p ratio | Random effects |
| Wyuts et al. | JMR, 2004 | Conjoint analysis | Key informant | 167 firms; 2,667 informants | Computer networks | Preferences in conjoint task | Repeated measures |

*JMR = Journal of Marketing Research; JSR = Journal Service Research; Mktg Sci = Marketing Science

Longitudinal data have also been analyzed via HLM models (cf. Van den Bulte, 2000). In education, the micro units are repeated measures observations (e.g., standardized tests on children in grades 5, 6, 7), and the macro units are the students themselves (three-tier multilevel models are fit if data on the schools were used as a superordinate macro level of analysis). In marketing, there are also longitudinal data, including the within-subjects factors in experimental designs alluded to previously. But easily the greatest source of longitudinal data in marketing is panel data. Panel data are an abundant supply of observations (e.g., purchase occasions), which are linked within households over time. Furthermore, many marketing modelers struggle with their supposition of a micro level model (e.g., the household-level decision maker), which is seemingly irreconcilable with their access to only aggregated, macro level data (e.g., at the "store" level" or at the brand "market-share" level). Yet in recent work, scholars have created estimation methods whereby aggregate data may be used to represent choices households make at the level of the product purchased (Bell et al., 2005; Chen and Yang, 2003; Yang, Chen, and Allenby, 2003; Musalem, Bradlow, and Raju, 2004).

To date, the micro and macro level models have been based on assumptions of linearity. To incorporate curvilinear relationships, clearly powers of predictors may be used to capture the nonlinearities. One line of methodological development in HLM would be to extend the models to allow for nonlinear relationships and categorical dependent measures.

Still other possibilities exist for the application of HLM models in marketing. Researchers might be interested in micro units of businesses, regions, or cultures, nested in macro units of industries or countries, and then marketing questions might be posed, for example, "Do different cultures pay attention to different attributes when purchasing laptops?," "How does the decision process differ in buying centers in South America vs. South East Asia?," "Is the association between a firm's market orientation and its financial performance stronger in computer hardware or software companies?," "Is the strength of a relational tie a predictor of continued business in service sectors but less predictive for goods?" For all of these questions, and many more, where a known structure exists in the data to be analyzed, HLM offers a viable technique for analysis–one that may well provide superior results to other techniques.

## Summary

This chapter has offered some insight into the use of hierarchical linear models to study marketing phenomena. This tool has been used extensively in sociology and educational realms, and has garnered some attention in the management literature, but has seen limited adoption in marketing research to date. HLM provides researchers with an elegant analytical tool for studying nested data, offering the ability to use all available data without throwing information away (via aggregation) or bending the rules of independence (via disaggregation). Our intentions in this chapter were to provide a tutorial on how to implement this technique, while also providing examples of existing research where the authors have employed HLM. Upon completing this chapter, we hope that researchers will be able to effectively use HLM on their own data.

Although we have provided a number of examples where HLM is an applicable technique, it is not without its limits. As mentioned earlier, even in data sets where a hierarchically nested structure naturally exists, HLM is only applicable if the dependent variable of interest is measured at the micro level. If the outcome variable of interest is a macro variable, aggregating is necessary, and the use of standard linear models is appropriate (e.g., OLS or structural equations models). Hence, this hammer is only appropriate for specific types of nails.

Despite these limits, HLM remains a powerful tool for analyzing hierarchically structured data, both within organizations and in studying customers. We hope that this chapter has provided an appropriate introduction to HLM, including its strengths and limitations, and that the examples and potential uses offered encourage other researchers to adopt the technique.

**Appendix 7.1 Steps to Run SAS Software[4]**

*This SAS syntax will fit the HLM models to the small data set illustrated in this chapter; data microex; input brno brand $ custid loyal income; income = income-47.42; cards;

| | | | | |
|---|---|---|---|---|
| 1 | Audi | 1 | 4 | 60 |
| 1 | Audi | 2 | 4 | 45 |
| 1 | Audi | 3 | 5 | 78 |
| . . . | | | | |
| 5 | VW | 4 | 5 | 41 |
| 5 | VW | 5 | 3 | 29 |
| 5 | VW | 6 | 4 | 37 |

*proc means; *var income; *previous to get income mean for centering;

```
data macroex; input brno prest; cards;
1 4
2 4
3 2
4 5
5 2
proc sort data = microex; by brno; proc sort data = macroex; by brno;
data all; merge microex macroex; by brno; *proc print data = all; run;

*level 1 model;
proc mixed data = all info method = reml covtest;
class brno custid; model loyal = income /solution chisq;
random int / subject = brno type = vc;
random int / subject = custid(brno) type = vc; run;

*full model (5c);
proc mixed data = all info method = reml covtest;
class brno custid; model loyal = prest income prest*income /solution chisq;
random int / subject = brno type = vc;
random int / subject = custid(brno) type = vc; run;
```

**Appendix 7.2 Steps to Run HLM Software[5]**

There is a text file, “cust-leve11.txt,” containing the level 1 data:

```
1 4 60 1
1 4 45 2
1 5 78 3
```

. . .
5 5 41 4
5 3 29 5
5 4 37 6

and another text file, "brand-leve12.txt," contains the level 2 data:

1 4
2 4
3 2
4 5
5 2

Double click and open the HLM software. To start a new job, click on the following menu options:

File → SSM → New → Ascii
Accept the default: HLM2

Name a response file: tryresp

- Enter the leve11 file name: cust-leve11.txt.
- Enter the number of variables: 3 (you do not count the macro/brand identifier).
- Enter variable labels: loyal, income, custid.
- Enter their FORTRAN format, per above, include the parentheses: (a1,f2.0,f3.0,f3.0).
- Leave the weighting options alone.
- Enter the leve12 file name: brand-leve12.txt.
- Number of variables is: 1 (again, do not count the macro/brand id).
- Enter variable labels: prestige.
- And the data's FORTRAN format: (a1,f2.0).
- Save the response file.
- Make a SSM file.
- Click on "Done" (HLM will make you "check stats" first, which is always a good idea).

Now there are two available pulldown menu boxes, which allow you to toggle between levels 1 and 2. Click on "loyal" and take the option "outcome variable."

To fit the "level 1 model":

- Click on "income" and choose "add variable, grand centered."
- Beta1 is clicked on, click on the "error" box (it removes the error from the b1 equation).
- Leave the error term on the b0 equation.[6]
- Click on "run analysis."
- Go to "file" for "view output" and print if you wish.

To fit the "level 2 model" in which the macro variable W is used to model the intercepts but not yet the slopes, add the following:

- With the "x" in the beta0 box, click on level 2, then click on "prestige" and add "uncentered"; run analysis; go to view output.
- To use W to also predict the slopes, click on the beta1 box (so the "x" appears there), click on level 2, click on "prestige," add it "uncentered," etc.

## Appendix 7.3 Relationships to Other Models

In this appendix we offer an exposition of how HLM models subsume a number of more familiar models (cf. Bryk and Raudenbush, 1992, p.17). First, recall the models presented in the chapter:

(2) *The Micro Level Model:* $Y_{ij} = \beta_{0j} + \beta_{1j}(X_{ij} - \bar{x}_j) + e_{ij}$.
(3) *The Macro Level Model, modeling the intercepts:* $\beta_{0j} = \gamma_{00} + \gamma_{01}W_j + u_{0j}$.
(4) *The Macro Level Model, modeling the slopes:* $b_{1j} = \gamma_{10} + \gamma_{11}W + u_{1j}$.
(5c) *HLM:* $Y_{ij} = \gamma_{00} + \gamma_{01}W + \gamma_{10}(X_{ij} - \bar{x}_j) + \gamma_{11}W_j(X_{ij} - \bar{x}_j) + u_{0j} + u_{1j}(X_{ij} - \bar{x}_j) + e_{ij}$

### *Ordinary Least Squares Regression*

If $u_{0j} = u_{1j} = 0$ , then (5c) reduces to a regular regression because there is only one error term: $Y_{ij} = \gamma_{00} + \gamma_{01}W_j + \gamma_{10}(\bar{x}_{ij} - \bar{x}_j) + e_{ij}$. Note, however, that there is still the logical and philosophical issue of treating the macro data as disaggregated to the micro level.

### *Means as Outcomes Regressions*

If there are no micro predictors (i.e., no *X*'s), then there will be no $\beta_{1j}$ term in model (2) which reduces to: $Y_{ij} = \beta_{0j} + e_{ij}$, nor would there be a model (4) to predict these nonexistent $\beta_{1j}$'s. The remaining macro level equation seeks to model the micro intercept as a function of the macro variable, the same equation (3) as before: $\beta_{0j} = \gamma_{00} + \gamma_{01}W_j + u_{0j}$. Together, the previous model (5c) is simplified to: $Y_{ij} = \gamma_{00} + \gamma_{01}W_j + u_{0j} + e_{ij}$.

### *Random Coefficients Regression Models*

If there are no macro predictors (i.e., no *W*'s), then there will be no slope parameters in the macro equations, resulting in a simplified (3) $\beta_{0j} = \gamma_{00} + u_{oj}$ and (4) $\beta_{ij} = \gamma_{10} + u_{1j}$. The micro equation (2) remains the same, $\gamma_{ij} = \beta_{0j} + \beta_{1j}(X_{ij} - \bar{x}_j) + e_{ij}$, and together, the substitution results in: $Y_{ij} = \gamma_{00} + \gamma_{10}(X_{ij} - \bar{x}_j) + u_{0j} + u_{1j}(X_{ij} - \bar{x}_j) + e_{ij}$. The model captures the idea that the macro units' intercepts (means, essentially) and slopes (reflecting the relationship between *X* and *Y*) vary randomly, but there is no attempt to predict the variability in terms of the macro variables (the *W*'s). See Longford (1993) for more statistical theory on these models.

### *One-Way Analysis of Variance (ANOVA) with Random Effects*

If there are no micro predictors (i.e., no *X*'s), and no macro predictors (*W*'s), then model (2) reduces to: $Y_{ij} = \beta_{0j} + e_{ij}$, and model (3) reduces to*:* $\beta_{0j} = \gamma_{00} + u_{0j}$, and there would be no model (4) given that there exist no terms. As a result, model (5c) simplifies to: $Y_{ij} = \gamma_{00} + u_{oj} + e_{ij}$. This model is a one-way ANOVA in which $\gamma_{00}$ is the grand mean, the $u_{oj}$'s (1 per brand *j*) are the group means, and are the error terms. Neither the micro nor the macro model has any predictors, other than group (brand) membership. The variance of $Y_{ij}$ is then $\mathrm{Var}(Y_{ij}) = \mathrm{Var}(u_{oj} + e_{ij}) = \tau_{00} + \sigma^2$, that is, an apportioning of "between and within" variability. The "intraclass correlation coefficient" is:

$$\rho = \frac{\tau_{00}}{\tau_{00} + \sigma^2} ,$$

a ratio of between vs. (between + within), or between over total, which is thus interpretable like an $r^2$. This is often recommended as a benchmark model to fit, to answer the question, "Do there even exist macro/brand differences to bother modeling?"

For more on these models and their relatives, see Raudenbusch and Bryk (2002). In particular, their technical appendix describes the relationships between how these models are fit and how the general (empirical) Bayes model is specified.

**Acknowledgments**

The authors are grateful to Eric Bradlow, Doug Bowman, Naresh Malhotra, and Christophe Van den Bulte for comments on this research.

**Notes**

1. And, of course, if our *J* car brands were randomly sampled from the universe of car brands, this sampling carries the useful by-product of allowing us to make broader generalizations of our findings later.
2. Cf. Bryk and Raudenbush (1992), pp. 10, 26ff.
3. Additional information on these data and measures is available from the authors upon request.
4. Little, Milliken, Stroup, and Wolfinger (1996); also see the fabulous introduction by Singer (1998)
5. Bryk, Raudenbush, Cheong, and Congdon (2000); the software is available at www.ssicentral.com, including a free student version which may be downloaded.
6. In general, click off the error term for fixed effects parameters, and add or retain error terms to equations representing random effects.

**References***

Achen, Christopher H., and W. Phillips Shively. (1995) *Cross-Level Inference.* Chicago: University of Chicago Press.
Arabie, Phipps, and Lawrence Hubert. (1994) "Cluster Analysis in Marketing Research." In *Advanced Methods in Marketing Research,* ed. Richard P. Bagozzi, pp. 160–189. Cambridge, MA: Blackwell.
Bell, David R., Andre Bonfrer, and Pradeep K. Chintagunta. (2005) "Recovering SKU-Level Preferences and Response Sensitivities from Market Share Models Estimated on Item Aggregates." *Journal of Marketing Research,* 42(2), 169–182.
Berry, Steven, James Levinsohn, and Ariel Pakes. (1995) "Automobile Prices in Market Equilibrium." *Econometrica,* 63 (4), 841–890.
———. (2004) "Differentiated Products Demand Systems from a Combination of Micro and Macro Data: The New Car Market." *Journal of Political Economy,* 112 (1), 68–105.
Bock, R. Darrell. (ed.) (1989). *Multilevel Analysis of Educational Data.* San Diego, CA: Academic Press.
Brown, Christina L. (1999) "'Do the Right Thing': Diverging Effects of Accountability in a Managerial Context." *Marketing Science,* 18 (3), 230–246.

*Raudenbusch and Bryk (2002), Heck and Thomas (2000), and Luke (2004) are particularly readable introductions.

Bryk, Anthony S., and Stephen W. Raudenbush. (1992) *Hierarchical Linear Models: Applications and Data Analysis Methods.* Newbury Park, CA: Sage.

Bryk, Anthony S., Stephen W. Raudenbush, Yuk Fai Cheong, and Richard Congdon. (2000) "HLM 5: Hierarchical Linear and Nonlinear Modeling." Lincolnwood, IL: SSI.

Calder, Bobby J., and Edward C. Malthouse. (2003) "The Behavioral Score Approach to Dependent Variables." *Journal of Consumer Psychology,* 13 (4), 387–394.

Chen, Yuxin, and Sha Yang. (2003) Estimating Disaggregate Models Using Aggregate Data via Augmentation of Individual Choice. Working paper.

Despande, Rohit, John U. Farley, and Frederick E. Webster. (1993) "Corporate Culture, Customer Orientation, and Innovativeness in Japanese Firms: A Quadrad Analysis." *Journal of Marketing,* 57 (1), 23–37.

Goldstein, Harvey. (1995) *Multilevel Statistical Models*. 2d ed. New York: Oxford University Press.

Heck, Ronald H., and Scott L. Thomas. (2000) *An Introduction to Multilevel Modeling Techniques.* Mahwah, NJ: Erlbaum.

Hofmann, David A., and Adam Stetzer. (1996) "A Cross Level Investigation of Factors Influencing Unsafe Behavior and Accidents." *Personnel Psychology,* 49, 307–339.

Jaworski, Bernard J. (1988) "Toward a Theory of Marketing Control: Environmental Context, Control Types, and Consequences." *Journal of Marketing,* 52 (3), 23–39.

Jaworski, Bernard J., and Ajay K. Kohli. (1993) "Market Orientation: Antecedents and Consequences," *Journal of Marketing,* 57 (3), 53–70.

Kohli, Ajay K. (1985) "Some Unexplored Supervisory Behaviors and Their Influence on Salespeople's Role Clarity, Specific Self-Esteem, Job Satisfaction, and Motivation." *Journal of Marketing Research,* 22 (4), 424–433.

Kohli, Ajay K., and Bernard J. Jaworski. (1990) "Market Orientation: The Construct, Research Propositions, and Managerial Implications." *Journal of Marketing,* 54 (2), 1–18.

Kreft, Ita (ed.) (1995) Special Issue of the *Journal of Educational and Behavioral Statistics* on Hierarchical Linear Models: Problems and Prospects, 20 (2), 1-113.

Kreft, Ita, and Jan de Leeuw. (1998) *Introducing Multilevel Modeling.* Thousand Oaks, CA: Sage.

Lee, Jangwoo, and Danny Miller. (1999) "People Matter: Commitment to Employees, Strategy, and Performance in Korean Firms." *Strategic Management Journal,* 20, 579–593.

Little, Ramon C., George A. Milliken, Walter W. Stroup, and Russell D. Wolfinger. (1996) *SAS System for Mixed Models*. Cary, NC: SAS Institute.

Longford, Nicholas T. (1993) *Random Coefficient Models.* New York: Oxford University Press.

Luke, Douglas A. (2004) *Multilevel Modeling.* Newbury Park, CA: Sage.

Malthouse, Edward C., James L. Oakley, Bobby J. Calder, and Dawn Iacobucci. (2004) "Customer Satisfaction Across Organizational Units." *Journal of Service Research,* 6 (3), 231–242.

Mohr-Jackson, Iris. (1992) "Broadening the Market Orientation: An Added Focus on Internal Customers." *Human Resource Management,* 30 (4), 455–467.

Musalem, Andres, Eric T. Bradlow, and Jagmohan S. Raju. (2004) On the Estimation of Individual-Level Choice Models on Aggregate Share Data Using Data Augmentation. Working paper, Wharton, University of Pennsylvania.

Narver, John C., and Stanley F. Slater. (1990) "The Effect of a Market Orientation on Business Profitability." *Journal of Marketing,* 54 (4), 20–35.

Nevo, Aviv. (2000) "Mergers with Differentiated Products: The Case of the Ready-to-Eat Cereal Industry." *Rand Journal of Economics,* 31 (3), 395–421.

———. (2001) "Measuring Market Power in the Ready-to-Eat Cereal Industry." *Econometrica,* 69 (2), 307–342.

Raudenbush, Stephen W., and Anthony S. Bryk. (2002). *Hierarchical Linear Models: Applications and Data Analysis Methods.* 2d ed. Newbury Park, CA: Sage.

Raudenbush, Stephen W., and J. Douglas Willms. (eds.). (1991) *Schools, Classrooms, and Pupils: International Studies of Schooling from a Multilevel Perspective.* San Diego, CA: Academic Press.

Rousseau, Denise M. (1985) "Issues of Level in Organizational Research: Multi-Level and Cross-Level Perspectives." *Research in Organizational Behavior,* 7, 1–37.

Seibert, Scott E., Seth R. Silver, and W. Alan Randolph. (2004) "Taking Empowerment to the Next Level: A Multiple-Level Model of Empowerment, Performance, and Satisfaction." *Academy of Management Journal,* 47 (3), 332–349.

Singer, Judith D. (1998) "Using Sas Proc Mixed to Fit Multilevel Models, Hierarchical Models, and Individual Growth Models." *Journal of Educational and Behavioral Statistics,* 24 (4), 323–355.

Slater, Stanley F., and John C. Narver. (1994) "Does Competitive Environment Moderate the Market-Orientation-Performance Relationship?" *Journal of Marketing,* 58 (1), 46–55.

Van den Bulte, Christophe. (2000) "New Product Diffusion Acceleration: Measurement and Analysis." *Marketing Science,* 19 (4), 366–380.

Van den Bulte, Christophe, and Stefan Stremersch. (2004) "Social Contagion and Income Heterogeneity in New Product Diffusion: A Meta-Analytic Test." *Marketing Science*, 23 (4), 530–544.

Wuyts, Stefan, Stefan Stremersch, Christophe Van den Bulte, and Philip Hans Franses. (2004) "Vertical Marketing Systems for Complex Products: A Triadic Perspective." *Journal of Marketing Research,* 41 (4), 479–487.

Yang, Sha, Yuxin Chen, and Greg M. Allenby. (2003) "Bayesian Analysis of Simultaneous Demand and Supply." *Quantitative Marketing and Economics,* 1 (3), 251–275.

# ABOUT THE EDITOR AND CONTRIBUTORS

**Richard P. Bagozzi** is J. Hugh Liedtke Professor of Management, Marketing, Behavioral Science, and Psychology at the Jesse H. Jones Graduate School of Management, Rice University.

**Adam Duhachek** is Assistant Professor of Marketing at the Kelley School of Business, Indiana University.

**Dawn Iacobucci** is Professor of Marketing at the Wharton School of the University of Pennsylvania.

**Tracey M. King** is a doctoral student in marketing at the College of Management, Georgia Tech.

**Myung-Soo Lee** is Professor of Marketing at the Zicklin School of Business, Baruch College, The City University of New York.

**Donald R. Lehmann** is George E. Warren Professor of Business in the Marketing Division of Columbia Business School.

**Deborah J. MacInnis** is Professor of Marketing at the Marshall School of Business, University of Southern California.

**Naresh K. Malhotra** is Regents' Professor in the Department of Marketing, College of Management, Georgia Institute of Technology.

**Gina L. Miller** is Assistant Dean and Associate Professor of Marketing at the Stetson School of Business and Economics, Mercer University.

**James L. Oakley** is Assistant Professor of Marketing at the Krannert School of Management, Purdue University.

**A. Parasuraman** is Professor and Holder of the James W. McLamore Chair in Marketing at the University of Miami.

**C. Whan Park** is the Joseph W. De Bell Professor of Marketing at the Marshall School of Business, University of Southern California.

**Vanessa M. Patrick** is Assistant Professor of Marketing at the Terry College of Business, University of Georgia.

**Brian T. Ratchford** holds the Pepsico Chair in Consumer Research at the Robert H. Smith School of Business, University of Maryland.

**Shun Yin Lam** is an Assistant Professor in the Marketing and International Division, Nanyang Business School, Nanyang Technological University in Singapore.

**Debabrata Talukdar** is Assistant Professor of Marketing at the School of Management, SUNY Buffalo.

# INDEX