THE SCREENING OF NEW PRODUCT CONCEPTS: INFORMATION USE AND THE EFFECTS OF EXPERIENCE AND EXPERTISE

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Abstract

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The effects of experience and expertise on managers' search for information while screening new product concepts were investigated using a computer-interactive screening simulation. Relationships between respondents' attributions about product success and failure, their judgments of the diagnosticity (predictive usefulness) of different types of information, and information search were also investigated. Sixty-two respondents from the microcomputer software industry and the pharmaceutical industry were involved in the study. They searched for information about three new product concepts, then evaluated the three concepts. The three concepts were designed to vary the decision context--one concept had predominantly favorable attributes, one had predominantly unfavorable attributes, and one was mixed.

The study showed that experience and expertise were related but distinct constructs which could have differing effects on information search and on concept evaluation. Under conditions of favorable and mixed attributes, increased expertise and experience led to less information search. Expertise was related to spending less time in search, while experience was related to spending more time searching for information. Both constructs were related to managers' perceptions of information diagnosticity. Both constructs were also related to the cutoffs used when screening new product concepts, though the relationships depended on the criteria for screening as well as the respondent's industry. Expertise was related to the evaluation of the new product concepts, while experience was not.

Managers' attributions for product success and failure were found to be very idiosyncratic. There was no evidence that their attributions were related to their levels of either experience or expertise. However, these attributions were related to judgments about the diagnosticity of information. The diagnosticity of information was also related to information search. Respondents were more likely to search information rated high in diagnosticity and to search it sooner.

Managers' ratings of the diagnosticity of different types of information are discussed. Managerial implications as well as theoretical contributions of the study are also included.

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Introduction

Much of the research in marketing, especially that in consumer behavior, deals with the decisions and decision processes of individuals. Marketing researchers have focused much attention on issues of how and why individuals make choices the way they do. We know a great deal about how consumers search for and evaluate information about product concepts, about the way this information is stored in memory, how it is retrieved, and how choices are made.

Unfortunately, very little of this understanding of individuals' cognitive processes has made its way into the study of managerial decision making. Largely, most of the literature in marketing on managers' decisions is oriented toward understanding the structure of managerial decision making, its outcomes, and the relationship between these outcomes and some goal state, such as profitability. The literature is also largely normative in nature. That is, the field has provided much literature on how managers *should* make decisions, but very little work has been done on how managers actually *do* make decisions.

This study seeks to add to our understanding of managerial decision processes. Though strategic marketing is receiving increased attention of late, very little of the work in the field acknowledges that the decision maker's cognitions or beliefs influence strategy formulation. Understanding managers' cognitive processes is extremely important because they determine the type and amount of information sought and evaluated, and therefore influence decision outcomes. Causal schema guide managers' strategic behavior because their beliefs about "how the world works" indicate which variables are used to predict outcomes and are manipulated to achieve given ends. Causal schema also affect how the manager interprets the outcome of decisions, thereby affecting the development of future beliefs and the use of these beliefs. Many important marketing activities, such as environmental scanning, marketing resource allocation, the adaptation of sales strategies to meet the needs of a given client, and responses to competitors' initiatives in the marketplace, are influenced by the way persons engaging in those activities select, perceive and process information in their environment.

Many researchers have pointed out the influence of managerial cognition on strategic decision making. In *Organization and Environment*, Lawrence and Lorsch propose that the perceptions of top executives are the best method for defining environmental uncertainty (Lawrence and Lorsch 1969). Anderson and Paine (1976) hypothesize that individual subjective factors influence strategy formulation through their effect on environmental and organizational perceptions. In their study of strategic change in a retail chain, Mintzberg and Waters (1982) suggest that in the entrepreneurial mode of strategy formulation, the development of a new strategy is usually carried out "in a single informed brain" (p. 496). More recently, Curren, Folkes, and Steckel (1992) have argued that decision makers are likely to have self-serving biases in their causal attributions for performance and that these biases affect expectations of future performance as well as planning behavior.

Other authors have recognized the importance of understanding managerial cognitive processes and have pointed out the scarcity of research in this area. Ungson, Braunstein, and Hall (1981) have pointed out the need for a better understanding of managerial cognitive processes to improve information gathering activities in firms. They argue that other researchers have shown that managers' functional disciplines bias their environmental scanning (Dearborn and Simon 1958; Hambrick 1982). Therefore, it is vital that we examine the heuristics and biases operating in environmental scanning to better understand managers' limitations in information gathering and processing and to aid in the development of information gathering systems that overcome these biases. Schwenk (1988) asserts that researchers have not paid sufficient attention to strategists' cognitive processes in the past and that the study of these processes may improve our understanding of industry and competitive strategy and the ways environmental factors affect strategic decisions.

Stubbart (1989) asserts that managerial cognition has always been a vital but neglected element in the study of strategic decision making. He argues that in many models of strategic management, the importance of managerial cognitions is implicit but never explicitly stated. Many models assume that the strategic planning process is a logical, analytical one based on the economist's ideal of rationality. Citing work that has shown that the application of this idealized, rational process does not necessarily lead to better performance (Kiechel 1982; Pearce, Freeman and Robinson 1987), Stubbart argues that managerial cognition is the "missing link" in strategic planning, a link that demands additional theoretical and empirical development.

An understanding of managers' cognitive processes is also important because most of the work in marketing on strategic decision making is normative in nature. Much of the literature in the field focuses on prescribing general approaches for planning (Busch and Houston 1985; Day 1977; Lilien and Kotler 1983; Wind and Mahajan 1981). Little work has delved into the behavioral processes behind marketing plans, though such behavioral processes may account for important differences among marketing managers and therefore among firms. Also, much of the normative literature implicitly assumes that strategic decision makers make decisions rationally. But, there is evidence that this is not so. After performing a case study of the decision making styles of a dozen senior level managers, Isenberg (1984) stated that "managers seldom think in ways that one might simplistically view as 'rational', i.e., they rarely systematically formulate goals, assess their worth, evaluate the probabilities of alternative ways of reaching them, and choose the path that maximizes expected return" (p. 82). If this is so, then prescriptions developed in the normative literature may be misguided. Without an understanding of how managers think and the cognitive and other limitations under which they operate, our normative prescriptions about how they should think may be of little value.

Conceptual Model of Human Decision Making

This study explores this "missing link" of managerial decision making. Specifically, it seeks to illuminate managers' cognitive processes during the evaluation of new product concepts. As a starting point, Figure 1 shows a conceptual model of human decision making adapted from the relevant literature in the decision sciences. This general model, adapted from Hogarth (1989), is accepted widely in the decision science literature. It shows that judgment occurs within a specific **task environment** (box 1). Within that task environment is the person's **schema** (box 2), which symbolizes the person's beliefs concerning the task environment and his/her representation of it. The actual processing of information includes the **acquisition** of information (box 3), the **processing** of that information (box 4) and the **output** (box 5). The individual's **action** (box 6) is the result of the judgment process. Subsequently the action leads to an **outcome** (box 7), which can feed back into the person's schema and may even affect the environment in which the action takes place.

Figure 2 shows a modification of this general model which provided the framework for this study. The modified model incorporates factors 2 through 5 in the model developed by Hogarth (1989), though I have elaborated many factors, making them more specific.

The Proposed Model

The model shown in Figure 2 represents the process through which a decision maker collects and processes information to evaluate new product concepts. Both this model and Hogarth's (1989) begin with the decision maker's **causal schema**. The schema contain organized chunks of information about the decision domain that aid the decision maker in categorization and other aspects of information-processing (Klayman and Schoemaker 1990). Causal schema can be thought of as subjective theories about how the world works; they derive from generalizing across one's experiences with the world. The schema contains the decision maker's beliefs about new product success and/or failure (**success/failure attributions**). The schema predisposes the individual to conclude that certain factors are related to success or failure; these attributions are then fed back into the schema.

The next two constructs, **perceived diagnosticity** and **information accessibility**, depart from the Hogarth (1989) model of judgment. Feldman and Lynch (1988) developed the accessibility-diagnosticity theory to explain the effect of measurement operations on revealed correlations among survey measures of belief, attitude, intention and behavior. The accessibility-diagnosticity (AD) theory will be discussed in greater detail in the literature review section; briefly, it states that the likelihood that any cognition about an object will be used as an input to any subsequent decision involving that object or a related object is a function of: (1) the accessibility of the input in memory, (2) the accessibility of other inputs, and (3) the diagnosticities of the input versus other inputs (Feldman and Lynch 1988). Here, an input is diagnostic for a judgment or decision to the degree that a decision maker believes that the decision implied by that input alone would accomplish his/her decision goals (e.g., maximize utility, choose a justifiable alternative, etc.) (Lynch, Marmorstein, and Weigold 1988).

Though the AD theory was developed to explain aspects of <u>internal</u> information search (the individual's search for information in memory), I believe it will be useful in describing <u>external</u> information search as well because it provides a mechanism to understand **why** search continues and what pieces of information may be accessed by the decision maker. Perceived diagnosticity determines the expected benefit of possessing a piece of information. As the model shows, the **perceived diagnosticity** of a piece of information affects the individual's search for and use of information. Search for information terminates when the accumulated diagnosticity of the information considered has reached some threshold, or when *n* searches have been attempted without reaching the diagnosticity threshold (Lynch, Marmorstein, and Weigold 1988).

The **accessibility** of the information in question should affect information search and use as well, because decreasing accessibility raises the cost of acquisition. Feldman and Lynch (1988) hypothesized that accessible information has a disproportionate influence on the judgments made about an object because a decision maker will not be motivated to engage in additional information search if relevant information is readily available. Therefore, the more accessible an input, the more likely it will be used in evaluation over other inputs that are less readily available, and therefore more costly to obtain.

As the model shows, the decision maker's **causal schema** containing the **success/failure attributions** influences the **perceived diagnosticity** of any particular piece of information. The schema contains the individual's theories about the decision domain, his/her cause-effect beliefs about how things work. Obviously, then, the schema should influence the decision maker's beliefs about the ability of different pieces of information to discriminate between good and bad concepts. For example, information about factors that the decision maker believes are important causes of some desired outcome should generally be perceived as more diagnostic of that outcome than information that is not considered important. Likewise, factors to which the decision maker attributes success or failure should influence **perceived diagnosticity**. Factors to which success is attributed should be perceived as highly diagnostic of success; factors to which failure are attributed should be perceived as highly diagnostic of failure.

Both **perceived diagnosticity** and **information accessibility** influence the **evaluative criteria** used in the evaluation of the concepts presented. The **evaluation criteria** include the number and type of criteria chosen (market, product, financial, etc.) and the specific criteria themselves. The AD theory predicts that the **perceived diagnosticity** of a piece of information should affect whether the decision maker chooses it for use in evaluation. The more highly diagnostic a piece of information is, relative to other inputs, the more likely it will be used. The AD theory also predicts that the **accessibility** of a piece of information, as well as the accessibility of other pieces of information, should also affect the specific criteria chosen for use in evaluation. The more accessible a piece of information is, relative to other inputs, the more likely that it will be used as an input to the decision.

Another construct of interest is information **search characteristics**, which includes such factors as the time spent in search (length), the degree of search (the amount of available information accessed) and the recursiveness of search (the repetitiveness of the decision maker's "path" through the information or how often he/she accesses the same piece of information). As discussed later, the decision maker's experience should influence search characteristics.

The next construct of interest in the model is the decision maker's choice of **evaluation strategy**; that is, the series of mental operations applied to the information obtained to develop an evaluation. Is the information combined in some compensatory strategy or is the processing done in a noncompensatory manner? This construct is identical to Hogarth's (1989) processing construct.

The **decision output** (the specific evaluation made) is influenced by both the **evaluation strategy** and the **evaluative criteria** chosen for examination. It is obvious that using different choice criteria could easily lead to a different evaluation. And given identical criteria, the use of a compensatory strategy may lead to a very different decision output than the use of a noncompensatory strategy, such as an elimination-by-aspects strategy.

The **decision output** leads to some **action** by the decision maker, which in turn leads to some outcome. This **outcome** can then feed back into the person's **causal schema** and **success/failure attributions**, either modifying the previously held beliefs they represent or reinforcing them.

Many factors appear to influence the decision making process, including task complexity (Biggs, Bedard, Gaber and Linsmeier 1985; Klayman 1985), perceived importance of the decision (Shields 1983), number of alternatives (Payne and Braunstein 1978; Johnson and Meyer 1984) and cognitive simplification processes (Schwenk 1984). For the purposes of this research, I chose to study the effects of another important variable that seemed likely to influence all the inputs to the evaluation. This variable is the decision maker's level of **experience.** I believe that the decision maker's level of **experience** is likely to influence directly most of the constructs in the model that precede the decision output, since with **experience** the decision maker generally gains expertise.

Though there is no single agreed upon definition of expertise, a reasonable working definition of an expert is one who possesses a good deal of both *procedural* knowledge as well as *declarative* knowledge about a particular domain (Hershey, Walsh, Read, and Chulef 1990; Szymanski and Churchill (1990). In a problem-solving context, declarative knowledge is knowing <u>which</u> facts are relevant, while procedural knowledge connotes an understanding of how those facts can be combined to produce a solution. A more thorough review of the relevant literature will be developed later, but at this point it is important to note that profound differences exist between experts and novices. In terms of this study, a fundamental difference documented in the literature is that experts have more highly developed **causal schema** than do novices. There are differences in the organization of information in memory and in the repertoire of rules for using that information, both of which can have profound effects on problem-solving (Chi, Feltovich, and Glaser 1981). Both the model developed by Hogarth (1989) and that shown in Figure 2 highlight the importance of the **causal schema** in information acquisition, processing, and the decision output. Therefore, any factor that influences the **causal schema** should have a profound influence on the entire decision making process.

As will be discussed in more detail later, many studies have found differences between experts and novices on variables related to other constructs in the model. These include differences in the amount and type of information searched or accessed when trying to make a decision (Brucks 1985; Hershey, Walsh, Read, and Chulef 1990; Isenberg 1986; Perkins and Rao 1990), the speed and accuracy of problem solution (Chi, Glaser, and Rees 1982), recall of relevant information (McKeithan, Reitman, Rueter, and Hirtle 1981; Fiske, Kinder, and Larter 1983), reactions to information inconsistent with category knowledge (Sujan 1985), the importance weights of different pieces of information used to make a decision (Perkins and Rao 1990; Szymanski and Churchill 1990), and their understanding of the information needed before problem solving begins (Hershey, Walsh, Read, and Chulef 1990).

Scope of the Current Study

The model of new product concept (NPC) evaluation shown in Figure 2 was the framework for this study. It is important to note that I did not design this study to investigate every relationship shown. The most notable exclusion from the study was the decision makers' **causal schema**. Accessing and mapping out individual decision maker's schema is a difficult and very time-consuming task. Techniques have been developed to accomplish this task, most notably Axelrod's (1976) method for representing cognitive maps diagrammatically. Developing cognitive maps is a very time-consuming and restrictive process, because the researcher must interact individually with respondents. This places great limitations on the format and scope of the investigation. Though this fact did not rule out completely the development of cognitive maps, the time it would have taken to develop them would have required sacrificing the investigation of other important relationships in the model. Therefore, I focused on the relationships among other concepts in the model.

The study also excluded relationships involving the **action** and **outcome** of the decision making process because the primary focus here was on the decision making process itself. To ensure that the scope of this study was of manageable proportions, it was necessary to narrow the focus of the investigation. Therefore, **external constraints** on information accessibility and **information accessibility** itself, were beyond the scope of this study. Given this framework for the proposed research study, the discussion will move on to the specific decision context in which this investigation took place.

The New Product Decision Context

The specific context for this investigation is the manager's evaluation of new product concepts. I chose this decision for investigation because it is one of both great practical and theoretical importance. Thousands of new product ideas are developed every year. Yet, only 1 in 7 are ever launched (Urban, Hauser, and Dholakia 1987). It is easy to see, then, that corporations and individuals devote vast resources to the weeding out of bad concepts and the further development of good ones. Managerial cognitive effort and information search is not the least of these resources. The enormity of the resources devoted to the development and screening of new product concepts suggests that it is in any manager's and organization's best interests to make this process as efficient and effective as possible. A selection process that is inefficient or ineffective at selecting good concepts and weeding out bad concepts may have tremendous repercussions in terms of wasted resources, wasted time, and losses in the marketplace. In a recent article on failures in new product development, Robert Cooper cited a Booz, Allen, Hamilton study that found that 46% of all new product development costs go to failures.[1]

The many models or methods developed to aid managers in selecting among new product concepts (Myers 1976; O'Meara 1961; Pessemier 1975; Servi 1990; Urban 1968; Urban, Hauser, and Dholakia 1987) are evidence of academic interest in new product development. These models and methods outline very rational, logical processes for managers to follow when making their choices. For example, Servi (1990) suggests a method of ranking alternatives using a concept called a "figure of merit." This figure of merit (FOM) derives from both financial and non-financial criteria. To find the FOM, all non-financial criteria must be quantified in some way. Then, both types of criteria are combined in some way to come up with the FOM, which are used to rank the alternatives.

Similarly, Urban, Hauser, and Dholakia (1987) describe a process called product profile analysis (PPA). In PPA, relevant criteria (including such dimensions as probability of commercial success, development/production costs, etc.) are developed. The criteria are then assigned importance weights depending on their perceived relative importance. Each concept has a score on each dimension that is the product of its rating on that dimension and the importance weight of that dimension. Summing these scores gives the total evaluation of each concept. The evaluation procedures described above are very typical of the literature in that each concept is evaluated on **all** relevant attributes, all inputs are quantified, and the final evaluation is determined by using a weighted additive decision rule. We do not know to what degree managers' unaided decision making approximates such procedures; but, the results in the consumer decision making literature tend to show that decision makers exhibit many limitations and biases that hinder their

[1]Power, Christopher (1993), "Flops," *Business Week*, Aug. 16, 1993, 76-82.

ability to process information in such a rational and complete manner (Tversky and Kahneman 1974).

We know very little about how managers actually evaluate new product concepts. Understanding what types of criteria they consider (e.g., competitive, financial, etc.), how they operationalize those criteria, and how they use them (e.g., singly or in some combination) is vital both to our understanding of the process by which organizations determine which concepts are worthy of further attention and resources and to our ability to improve this process.

Also, though it is well-known that the failure rate for new products is very high (one study found it to be as high as 46%[2]), we know very little about what factors practitioners believe to be the causes of failure and why. Since there is evidence that managers are likely to have biases in their causal attributions for performance and that these biases may affect expectations of future performance (Curren, Folkes, and Steckel 1992), it is important to investigate managers' attributions and to see how they influence subsequent actions in the decision making process. A better understanding of these attributions may allow us to develop decision aids that reduce or eliminate these biases or their effects. Again, it is instructive to note that the normative literature provides information about what criteria *should* be used in evaluation and choice and what factors *should* be associated with product failure (see Urban, Hauser, and Dholakia 1987, p. 37-8), but there is little work on the congruence between normative prescriptions and managerial reality.

The effect of experience on the entire process of new product concept evaluation has the potential of offering valuable insight into many important issues. Understanding the differences between more experienced and less experienced decision makers may allow us simplify novice decision makers' learning processes, diminishing the time it takes them to gain expertise. Contrasting their decision

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[2]National Association of Advertisers, Inc. (1984), *Prescription for New Product Success*, New York: Association of National Advertisers, Inc.

processes may also yield insight into the adequacy of the many normative methods described in the literature. If normative methods are the most effective way to make these decisions, we would expect experts' decisions to more closely resemble them.

Shanteau and Stewart (1992) argue that research on expertise is important for many reasons. First, they argue that analyses of expert decision making provide an important means of establishing the generality of many commonly accepted findings in decision making research. Secondly, the study of expert decision making can provide useful information for the building of expert systems. This is an especially important point for the study of expert decision making in the new product context, where researchers are beginning to develop expert systems for selecting new products (Ram and Ram 1989; Mahmood and Sullivan 1992). Finally, Shanteau and Stewart (1992) argue that expert decision making should be studied because in our increasingly complex society, people are forced to rely on the judgments of experts. In all likelihood, this holds true in organizations, wherein busy managers often rely on the inputs of expert (or experienced) colleagues or subordinates.

I designed this study to make important contributions to several bodies of literature of both academic and managerial relevance. I discuss these contributions in the following section.

Research Questions and Intended Contributions

To summarize this introduction, the general research questions that guided this work were:

1. To what factors do managers attribute the success or failure of new products? Do attributions about new product success or failure differ for decision makers with different levels of experience?

2. How do the decision maker's attributions of product success or failure relate to his or her perceptions of the diagnosticity of specific pieces of information?

3. Which information is perceived as most and least diagnostic? How do expert and novice managers differ in the perceived diagnosticity of different types of information they use in their evaluations? Are the criteria they use similar to those that appear in the normative literature?

4. How do information search characteristics, such as the amount of information accessed, the time spent searching, and the order of search differ at different levels of decision maker experience?

5. How does the perceived diagnosticity of a piece of information relate to its use in the evaluation of new product concepts?

6. How do the number and type of criteria (financial, cost, competitive, market-related, risk-related, technological, political, etc.) used to evaluate and choose among new product concepts change at different levels of experience?

7. Does the specific evaluation strategy (i.e., additive, elimination by attribute, conjunctive) used by the decision maker differ by the decision maker's level of experience? If an evaluation strategy that makes use of cut-offs is chosen, do more experienced and less experienced decision makers have different cut-offs? How close are these rules to those assumed in normative models of new product evaluation?

I chose new product concept evaluation as the context for this decision to provide other useful contributions besides those discussed in the previous section. Though the literature documents the previously mentioned differences between experts and novices, in most of these studies the tasks performed by the subjects were somewhat well-structured and simple, such as solving simple physics problems or categorizing product information. Most strategic decisions can best be described as ill-structured or nonprogrammed (Simon 1960; 1973). Programmed decisions are routine and structured with a well-defined starting point, a clear goal, and standardized rules for reaching the goal. Nonprogrammed decisions, however, have few guidelines. They require that the decision maker rely on general problem-solving abilities and judgment. There is often disagreement among decision makers about the proper solution of such problems due to ambiguity about both the rules for problem solution and the potential consequences of any given action (Voss and Post 1988).

The distinction between well-structured and ill-structured decisions is a very important one, especially when considering the kinds of decisions marketing managers must make. Decisions such as generating advertising appeals, recommending a strategy for negotiation between channel members, or determining the appropriate target market for a product or service, involve incomplete information and a reliance on judgment. There is often no one right answer or right way in which to solve the problem; any solution could spark disagreement and debate among a group of decision makers.

Some researchers have argued that ill-structured or randomly organized problems reduce the differences between experts and novices in cognitive processing because in these types of problems experts are unable to use their skill advantages (Chase and Simon 1973). This may seem counterintuitive since it is reasonable to assume that experts' presumed greater familiarity with the decision domain and their more well-developed knowledge structures would simplify their search for and use of information in decision making, i.e., experts can create structure more easily or can discern the underlying structure in a task (Chi, Glaser, and Rees 1982). However, there has been some evidence to support this contention in psychological diagnosis (Hillerbrand and Claiborn 1990). Still, there is only limited research on managerial decision. Very little work has been done on more complex, strategic decisions (Isenberg 1986; Perkins and Rao 1990) so we do not know whether expertise effects will be found when the task is more complex, intricate, or ill-structured. I designed this study to fill this gap to help us better understand the boundaries of expertise effects.

Using the AD theory (Lynch and Feldman 1988) in this new product context extends it into a new environment, that of external information search and use. This extension therefore serves the function of testing the boundaries of the theory. Validation of the relationships shown in the model would also give us insight into managers' search for and use of information in decision making, and help to make sense of the differences between experts and novices in information search and use. Studies comparing experts and novices suggest that experts have more highly developed cognitive structures that allow for effective problem structuring and successful problem solution (Chi, Glaser, and Farr 1988). Another factor that may cause experts and novices to use different information in decision making is the perceived diagnosticity of that information. Because experts can be expected to have a better understanding of the decision domain, they should be better judges of which pieces of information are diagnostic. The relative diagnosticities of different pieces of information can be expected to influence their perceived importance and their use in decision making. This may explain the finding that experts are more likely to restrict their search to relevant and important information (Chiesi, Spillich, and Voss 1979).

To summarize then, I designed this study to make contributions to several different areas of interest. First, it designed to gain a more in-depth understanding of an important but largely unexplored area in the marketing literature, the process of strategic, managerial decision making. Another intended contribution was the extension of our understanding of the differences between experts and novice to a different domain, that of ill-structured, nonprogrammed decisions (Simon 1960; 1973). There is some doubt that the differences between novices and experts found in more structured task contexts will be obtained. Third, the accessibility-diagnosticity theory (Feldman and Lynch 1988) was to be tested in <u>external</u> information search.

I also hoped that there would be contributions of a substantive nature. Understanding the differences between experts and novices may simplify novice decision makers' learning processes, diminishing the time it takes them to gain expertise. If these differences can be delineated, it may be possible to develop better training programs for inexpert decision makers. Contrasting experts' and novices' decision processes may also yield insight into the adequacy of the many normative methods for new product decision making described in the literature. If normative methods are the most effective way to make these decisions, we would expect experts' decisions to more closely resemble them. A final contribution would be to shed light on the decision processes that underlie decision makers' judgments about new product concepts. Though new product development is a very important function in organizations and in the marketing literature, we know very little about these processes and how they compare with normative models.

In the next section, literature relevant to the above research questions will be reviewed. Literature on new product evaluation, expertise, and the accessibility-diagnosticity theorem (Feldman and Lynch 1988) will be reviewed. Critiques of these areas, which are discussed after the literature review, helped guide the methodology for this study.

Literature Review

In this chapter, I will review the four main bodies of literature relevant to this study. This includes literature on new product concept evaluation, attributions about new product success and failure, the effects of expertise or experience on decision making, and relevant research on decision process.

New Product Concept (NPC) Evaluation

Literature in the area of new product development (NPD) is extensive and broad, covering many different topics. A significant body of work deals with the process itself (Cooper and Kleinschmidt 1986; Hegarty and Hoffman 1990; McGuinness 1990; Smith 1988; Wind and Mahajan 1988; Zirger and Maidique 1990) as well as factors that influence it, such as communication between different functional units (Hise and O'Neal 1990; Moenaert and Sounder 1990). Other authors have investigated the speed with which the process delivers new products to the market (Bronikowski 1990; Gupta and Wilemon 1990; Schoonhoven, Eisenhardt, and Lyman 1990). Still others have focused on models or methods that may be used in the process (Ley and Ofir 1986; Choffray and Lilien 1986; Price 1985; Cooper 1985; Green and Krieger 1985).

A smaller body of work deals with issues directly relevant to the research questions outlined above, the evaluation of new product concepts (NPCs) and the factors leading to new product success or failure. In this section, this smaller body of work will be reviewed.

Evaluative Criteria: Most of the literature dealing with the evaluation of NPCs has been normative in nature. Normative prescriptions about the way new product concepts should be evaluated can be found in any of several texts dealing with new product development or product strategy (Busch and Houston 1985; Servi 1990; Urban, Hauser and Dholakia 1987; Wind 1982). Most of these texts suggest the rational, compensatory approach described in the introduction. These approaches almost always involve ranking the concepts using some factor (called a "desirability factor" by Wind (1982) or Servi's (1990) "figure of merit"). This factor is usually found by multiplying the product's rating on some criterion by that criterion's importance weight and summing across all evaluative criteria.

Table 1 gives an integrated listing of the dimensions that several authors suggest for use in NPC evaluation. To facilitate discussion, they have been grouped by type (competitive, financial, etc.). The first evaluative dimension, the concept's **match to organizational objectives and capabilities**, primarily encompasses those factors necessary to determine if the NPC is consistent with the organization's profit and market share goals as well as with its capabilities in such areas as marketing, technology/R&D, and managerial skills. The concept's **match to existing products or product lines**, the second dimension, seeks to assess the consistency of the NPC's resource needs with those of existing products. Included in this grouping are such factors as the NPC's effect on sales of existing products, its compatibility with other products, and whether its resource and distribution needs are consistent with those already existing. **Market characteristics** make up the third dimension for evaluation. This includes such factors as the market's sales potential, its scale, stability and penetrability. The fourth dimension is **investment analysis**, which includes standard financial criteria which may be used to evaluate an investment, including the concept's net present value, the period required to payback the investment, and cash flow analysis. **Competitive factors** comprise the fifth dimension. This includes such factors as the number of existing or potential competitors, their size and resources, and the likelihood of competitive entry into the market as well as the likelihood of competitors' retaliation. **Profitability** is the sixth dimension. It includes the size of the product's margin and the firm's potential for profits with this concept. The seventh and final dimension for evaluation is the **risk** associated with the introduction of the NPC. This includes factors which assess the concept's acceptance in the marketplace (i.e., compatibility with existing attitudes and methods of use, amount of learning necessary for product use, and its acceptance by existing channel members) as well as the likelihood of technical completion or commercial success. It also encompasses factors relating to the stability of the product, such as the stability of consumers' demand, the rate of technological change in the product-market, and the possibility of adverse regulation. The complexity of the necessary market research to guide product design and/or strategy is also included in this dimension. Overall risk increases as the complexity of the market research needed increases because it becomes more difficult to obtain accurate market information under these conditions.

Though most authors suggest that decision makers use most or all of these dimensions in their evaluations of NPCs, the relative importance of each dimension is left to the subjective evaluation of the decision maker. Busch and Houston (1985) suggest that the concept's **match to organizational objectives and capabilities**, the first evaluative dimension listed, is the most important and should be considered first, followed by market characteristics, which is the next most important.

Beyond the normative literature described above, there is little empirical work on the evaluation of NPCs. Three studies have dealt with empirical assessments of managers' use of evaluative criteria. In a study of managerial information use conducted by Perkins and Rao (1990), both expert and novice managers in the consumer packaged goods industry were presented with information on several NPCs and were then asked to determine the probability of their introducing each NPC.[3] Seven pieces of information were presented to the managers for each concept: three related to market research (Nielsen store audit data, diary panel data, consumer research), one related to the competition (whether the competitor had introduced a similar new product), and three had to do with others' support of or opinion about the new product (headquarters support, peer opinion, merchandiser word of mouth). Regressing the managers' subjective probabilities of introduction on the information presented, the authors found that of these seven pieces of information, managers weighted the "hard" data heavily--the

[3] In this section, overall findings for all managers will be presented. Differences between experts and novices will be discussed in the section on expertise.

Nielsen store audit data, diary panel data and consumer research data were all found to have significant regression coefficients. Of the three, positive results of research on consumer attitudes was found to be more important (beta = 11.41, $p<0.01$) than were either above average use of the product as reported by diary panel data (beta = 11.11, $p<0.01$) or above average sales figures from Nielsen store audit data (beta = 9.49, $p<0.01$). The existence of a similar competitive new product was also significant, and was negatively related to the probability of introduction (beta = -6.02, $p<0.05$). Of the "soft" data, only the merchandiser word of mouth was significant (beta = 11.82, $p<0.01$). Neither headquarters support nor peer opinion had significant coefficients. The results of this study indicate that, in general, "hard" data is more significant in the evaluation of new products than is "soft" data. All factors related to consumer research and the competition were found to be significant. Only one of the "soft" pieces of information were significant.

Another study of managers' evaluations of NPCs was done by Ronkainen (1985), in which the author investigated the changes in evaluative criteria across the stages of the new product development (NPD) process. The sample consisted of thirty managers in each of four Fortune 500 companies producing high-technology items (120 managers in all). First, the author conducted extensive interviews to develop an understanding of the temporal sequence of events in the process and to generate a preliminary list of evaluative criteria used. From these interviews, a model of the process was developed. This model consisted of five phases: the concept phase, the feasibility phase, the product/process phase, the scale-up phase, and the standardization phase. (Unfortunately, the author gave no further description of these phases or the decisions or activities involved in each.)

Next, managers were asked to indicate which of the criteria culled from the interview process were used to make GO/NO GO decisions during the various stages of the process. The author then grouped the criteria into three major groups (product, market, and financial criteria) and asked managers to allocate 100 points among the groups depending upon their importance during each phase.

Table 2 shows the specific criteria that managers said they used to make GO/NO GO decisions, Ronkainen's classification of those criteria into the three groupings, and the allocation of "importance points" among the three groups for the five stages of the NPD process. These results show that there were clear shifts in the importance of the different types of criteria through the process. Market criteria were most important during the concept phase, receiving an average of 51 points, while product criteria received 34 points and financial criteria received only 15 points. During the feasibility phase, product criteria increased in importance and maintained this increase until the scale-up phase, when they were roughly equal in importance to financial criteria. However, in the standardization phase, financial criteria were most important, while product criteria were found to be least important.

In a very interesting study of the NPD process in entrepreneurial high-tech firms, Pavia (1991) found results similar to the findings of Ronkainen (1985). In a survey of small, young firms specializing in high-tech manufacturing or software development, the author presented company presidents with a list of 14 criteria that could be used to evaluate a new product. She asked them to rate the importance of each criterion in their evaluation of potential new products on a 5 point scale, where 1 = not important and 5 = vitally important.

Before discussing the results of this study, it is important to note that Pavia (1991) conceptualized the NPD process as consisting of seven steps: new product strategy development, idea generation, screening, business analysis, development, testing, and commercialization. This conceptualization implicitly assumes that screening occurs at one time and one time only during the process. This is in contrast to Ronkainen's (1985) finding that evaluation of the concept or screening happens at every stage of the process. Also, notice that Pavia (1991) conceptualizes the business analysis of the new product as being distinct from screening. Therefore, one might expect that financial criteria might not be rated as being very important at this early stage.

Though the author did not present the results in such a way that the average importance of each criterion across respondents can be determined, the results do show that the majority of respondents focused less on financial criteria and more on product/market criteria. For example, 83% of the respondents rated the criterion "It will be likely to attract new customers" as vitally or quite important, while only 34% rated "It will meet a certain level of sales, profits or market share in 4-10 years" as being so. These findings are consistent with Ronkainen (1985) which showed that market and product criteria are deemed more important than financial criteria in the early stages of the development process.

Pavia (1991) also investigated whether the firm's approach to NPC evaluation was formal or informal. She asked respondents to rate their level of agreement with two statements characterizing their firms' approach to the screening of new product concepts: "Our firm relies heavily on 'gut feel' to evaluate potential new products" and "Our firm uses a consistent set of criteria to evaluate potential new products." Surprisingly, more than half the respondents (57%) indicated agreement or strong agreement with the statement that they relied on "gut feel" to evaluate NPCs. Only 36% agreed or strongly agreed that they used a consistent set of criteria for evaluation. (Only 13% agreed or strongly agreed with both statements, which indicates that most firms used one approach or the other.) This is surprising because it gives clear indication that, at least in the majority of firms sampled in this study, the evaluation of NPCs is not at all a rational act undertaken using a consistent set of criteria. This may be more true of small, entrepreneurial firms, like those sampled in this study, than of larger organizations. Because of their limited resources (human and financial) and relative lack of bureaucracy, entrepreneurial firms may be less likely to have a formal screening procedure which would call for researching each NPC on a list of evaluative criteria.

Interestingly, the author related the use of specific screening criteria with agreement on the above statements characterizing the evaluation process in the firm. She found that agreement with the statement about using "gut feel" was significantly and negatively correlated ($p<0.05$) with the four financial criteria indicating that "gut feel" firms seem prone to disregard financial criteria. Agreement on the statement regarding the use of a consistent set of criteria was significantly and positively related ($p<0.05$) with the use of the four financial criteria as well as the criteria that the new product offer entry into a high potential and growing market. (Unfortunately, the strength of these relationships cannot be determined since the author did not provide the correlations between the items.)

Finally, Pavia investigated whether the respondents' educational backgrounds had any effect on the use of specific screening criteria. She found that firms in which the decision maker had an educational background in business rated two of the four financial criteria ("It will meet a certain level of profits within 1-3 years" and "It will meet a certain level of sales within 1-3 years") as being more important than did those who did not have a business background. There were no differences on the ratings of other criteria.

Summarizing the findings of these three studies, we see that:

1. The importance of different criteria in the evaluation of NPCs may depend on the specific stage of the NPD process (Ronkainen 1985).

2. In early stages of the process, market and product criteria are more important than are financial criteria (Ronkainen 1985; Pavia 1991).

3. In these three studies, evaluative criteria could be categorized into three groupings: product, market, and financial criteria. Product criteria included such factors as the product's attractiveness to certain market segments or its uniqueness. Market criteria included factors such as the market's size, growth rate or acceptance by the market (i.e., merchandiser word-of-mouth). Financial criteria included such factors as the product's likelihood of meeting profit goals or the total investment required.

4. An educational background in business may be related to an increase in importance of financial criteria in the evaluation of NPCs (Pavia 1991).

While it is relatively easy to compare the studies of Ronkainen (1985) and Pavia (1991), it is more difficult to integrate the results of Perkins and Rao (1990) because the methodology used in that study is different. The criteria to which the managers were exposed were much more limited in number and type and were also much more specific to the industry involved, the consumer packaged goods industry. For example, Nielsen store audit data, which was one of the pieces of information presented to the managers by Perkins and Rao (1990) would not be relevant to managers in high-tech firms, the sample in both the Pavia (1991) and Ronkainen (1985) studies. Therefore, the specific evaluative criteria used seem to depend to some degree on the industry being studied.

Though these studies give insight into the types of information managers use in their evaluations of NPCs, there were limitations caused by the specific methodologies employed. Perkins and Rao (1990) presented cards labeled to indicate the type of information they contained to the subjects. In both Pavia (1991) and Ronkainen (1985), the questionnaires presented to the subjects simply listed all the criteria which might be used in evaluation. In these studies, then, all information was displayed simultaneously. This may induce managers to make use of information they would not ordinarily use because it is made salient and is easily available. This makes interpretation of what types of information managers *actually* use in their evaluations difficult. The criteria were *framed* for the subjects, rather than allowing them to express the criteria in their own way. To avoid these limitations, a methodology in which each manager has to specifically ask for a piece of information without cueing or in which managers would have to list and rate evaluative criteria without being cued by the researcher would have to be developed. This would no doubt be very time-consuming and technically difficult. The techniques used in the studies discussed above, though they may have induced bias, were much easier to use and allowed the researchers to survey a much larger sample of respondents than otherwise could have been used.

Also, all three studies limited the number and type of information available to subjects. Comparing the seven pieces of information available to the subjects in

Perkins and Rao (1990) with the extensive criteria for evaluation in Table 1, it is obvious that a great many factors which the normative literature suggests should be used in evaluation could not be considered by the managers since they could not ask for information other than that provided on the IDB. Though both Pavia (1991) and Ronkainen (1985) did provide the managers with access to more of the criteria cited in the normative literature (14 items and 15 items, respectively) they were still not presented with comprehensive lists. There is some justification for use of the abbreviated lists of criteria since researchers in each study developed their instruments after extensive study of the industries and companies involved. Still, both this limitation and those discussed above limit the resemblance of the subjects' decision task to that which would occur in the real world.

Attributions of Success and Failure for New Products

Factors related to new product success or failure are outlined in almost any text on product design or development. Table 3 gives an integrated list of several causes of product failure culled from the works of several authors (Busch and Houston 1985; Davidson 1976; Urban, Hauser, and Dholakia 1987) and brief explanations of each. They include such factors as a target market that is too small, a product that is a poor match to the company's strengths, and a lack of channel support for the product.

Empirical work in the area of new product success or failure is more abundant than that on the evaluation of NPCs. It is important to note that the majority of research in this area is conducted by asking practitioners what factors they **believe** cause new products to be successful or to fail. It is a distinction that needs to be considered. As far as this author has been able to discern, no major study on new product success/failure has been carried out using an expert panel or some other source outside the organization to evaluate the new product or its development process to objectively assess factors influencing the product's success or failure. Of course, even the use of outside panels of experts is problematic because they would also be reporting beliefs; because the process is so complex, objectivity may be impossible.

Table 4 provides a summary of selected works in this area. I chose Cooper (1978) for review because it was the first study of this subject in the marketing literature. As such, it became the prototype for subsequent work in the field. In the interests of investigating the generalizability of Cooper's (1978) findings to different populations, I included the other studies (Cooper and de Brentani 1991; Link 1987; Zirger and Maidique 1990). All of these studied samples were different in some important way from that of Cooper (1978), who surveyed Canadian industrial products manufacturers. Link (1987) surveyed industrial manufacturers in another country, Australia. Zirger and Maidique (1990) studied equipment manufacturers in the United States. Finally, Cooper and de Brentani (1991) surveyed marketers of industrial financial services (financial services sold to organizational buyers, not individual consumers). Note that none of these markets included marketers of new products to individual consumers. It may be that the factors which cause new products to be successful or to fail in the consumer markets are different from those influencing success and failure in industrial markets.

The works listed here, as well as most of the work in this area, all make use of a common methodology. The study is usually conducted by surveying a firm's top managers (CEOs/presidents, marketing managers, or new product development managers). This respondent is asked to think of two new product projects in which his/her firm has recently been involved, one project a success and the other a failure. Then s/he is asked to rate both the successful product and the failure on several dimensions hypothesized to be related to new product success/failure. In the following review, all studies employed this methodology unless stated otherwise.

In the interests of brevity, I will discuss in detail only the first study in the marketing literature to address these issues, that of Cooper (1978). For the others I will report the consistency (or lack thereof) of their findings with those of Cooper (1978).

Cooper (1978) surveyed top managers of firms producing industrial products. Respondents were instructed to select two recent new product projects completed by their firms, one project a commercial success, the other a failure. Success and failure were defined from the point of view of the firm in terms of profitability (the degree to which a product's profitability exceeded, or fell short of, the minimum acceptable profitability for that type of project or investment, regardless of the way the firm measured profitability). The author then asked the respondent to characterize both the successful and the failed product on each of 77 variables that were hypothesized to influence new product success/failure. Variables were measured by presenting a phrase or sentence and requesting the manager to indicate whether the description applied to the product. Agreement was on an 11-point scale, where 0 = agree and 10 = disagree. The 77 variables were conceptualized by the author as belonging to six groupings, which were:

1. the commercial entity: the result of the new product process (the product being offered). It included attributes and advantages of the new product as well as the nature of its launch effort.

2. information acquired: the nature or quality of the information acquired or known during the new product process (e.g., whether the firm had accurate data on market potential, on buyer behavior, etc.).

3. proficiency of process activities: how well certain activities were undertaken during the new product process from idea generation to launch.

4. nature of the marketplace: the characteristics of the new product's market, such as the degree and nature of competition or the size of the market.

5. resource base of the firm: the compatibility of the resource base of the firm with the requirements of the project (i.e., the company/product fit).

6. nature of the project: the characteristics of the new product project, including such factors as the magnitude of the project or the complexity of the technology.

A factor analysis of the decision makers' responses on these 77 variables yielded 18 factors. These 18 factors explained 71.3% of the variance in the original variables. To determine each factor's ability to distinguish between new product successes and failures, discriminant analysis was performed. The resulting discriminant function included 11 of the 18 factors and correctly categorized 84.1% of the products (Wilks' lambda = 0.51, $F_{11,183} = 15.95$, $p = 0.001$). Table 5 shows the results of the discriminant analysis, including the factors in the equation, their coefficients, and centroids for the two groups (successes and failures).

The factor with the largest coefficient (0.527), meaning that it was the most powerful factor in discriminating between success and failures, was **Product uniqueness/superiority**. Unique, superior products were those that were new to the market, offered unique features to the customer, and were superior to competing products in meeting customers' needs. The coefficient for this factor was positive, indicating that it was positively related to new product success. Products which were more unique and superior to competing products were likely to be successes.

The second most important factor was **Marketing knowledge and marketing proficiency.** Products which scored highly on this factor were those in which the organization performed various marketing activities well, such as the preliminary market assessment and test marketing, or in which the organization understood relevant information, such as buyers' price sensitivity and the market's competitive situation. Again, the positive coefficient indicates that this factor is positively related to new product success.

The third factor, **Technical/production synergy and proficiency** incorporates variables having to do with the match between the product's technical and production needs and the organization's resources. Products which scored high on this factor were those in which the organization possessed compatible engineering skills, production resources and facilities for the project. It also included variables assessing the organization's proficiency at the various technical tasks that must be performed, such as in-house prototype testing or the production start-up. The results of the discriminant analysis show that this factor is again positively related to success.

Comparing Cooper's (1978) second and third factors with the suggested normative criteria listed in Table 1, one can see that there is much overlap.

Specifically, **Marketing knowledge and proficiency** and **Technical/production synergy** incorporate some of the same variables that make up the first evaluative criterion suggested by the normative literature, **Match to organizational objectives and capabilities.** Managers' beliefs that these factors are related to new product success lends support for the use of this first criterion in the evaluation of NPCs.

The fourth factor useful in discriminating between successful and unsuccessful new products was **Market dynamism.** Scoring high on this dimension indicated that there were frequent new product introductions in the market and that users' needs changed rapidly. The structural coefficient was negative, indicating that successful products avoided these dynamic markets. This factor is conceptually related to **Risk**, the seventh normative criterion listed in Table 1, which included variables having to do with the stability of demand and the rate of technological change in the product-market.

Market need, growth, and size was the fifth factor found to discriminate between successes and failures. This factor described markets which were large, had a high growth rate and in which customers had great need for the product type. Again, a positive structural coefficient indicates that this factor is positively related to success. This factor is similar to the third evaluative criterion suggested by the normative literature, **Market characteristics.**

The sixth factor was **Relative price of the product.** Products which scored high on this factor did not allow the customer to cut costs using the product and were priced higher than competing products. This factor entered the discriminant function with a negative coefficient, indicating that successful products were not priced higher than their competition and allowed their customers to cut costs.

Cooper's (1978) seventh factor, **Marketing and managerial synergy** is again related to both the first and second evaluative criteria suggested by the normative literature, **Match to organizational objectives and capabilities** and **Match to existing products or product lines.** Products which scored high on this factor were those in which the firm had adequate financial resources, necessary market research and managerial skills, and compatible resources in its sales force, distribution and advertising functions. The coefficient indicates that this factor is again positively related to product success.

The next factor to enter the discriminant function was **Market competitiveness and customer satisfaction**. Products which were introduced in highly competitive markets in which there were many competitors, intense price competition, and in which customers were satisfied with competitors' products scored high on this dimension. This factor had a negative coefficient, indicating that it was negatively related to success. Successful products avoided these types of markets. This factor is related to both the fifth factor suggested by the normative literature (Table 1), **Competitive Factors**, as well as the third factor, **Market Characteristics** (specifically the vulnerability of the market's competitors to penetration).

Newness to the firm, the ninth factor, described those products in which the potential customers, the product class, the production process needed to develop the product, the product technology, and the distribution and advertising necessary for the product were all new to the organization. This factor entered the discriminant function with a negative coefficient, suggesting that this factor was negatively related to success. This factor is conceptually the opposite of the first two evaluative criteria suggested by the normative literature, **Match to Organization Objective and Capabilities** and **Match to Existing Products or Product Lines** (Table 1). Both these evaluative criteria include dimensions which assess the management's experience with a product in market as well as its ability to use existing technology and existing distribution systems.

The tenth factor was **Strength of marketing communications and launch effort**. It described products in which the firm had strong launch efforts in both its sales force and its advertising/promotional effort as well as adequate advertising skills. Its positive coefficient indicates that it is positively related to success. This is related to the first evaluative criterion shown in Table 1, **Match to Organizational Objectives and Capabilities**.

The final factor to enter the discriminant function was **Source of idea/investment magnitude**. This factor is made up of only two variables, one having to do with whether the idea was market-derived and the other assessing the relative magnitude of the firm's investment in the NPD project. Though this factor did enter the discriminant function and did have an eigenvalue greater than 1.0, it is not clear that it is a particularly strong factor. The author states that while it is apparent that successful new products tended to be market-derived (a mean of 7.19 on a 0-10 scale, where 10=market-derived), product failures were *also* likely to be market-derived (a mean of 7 on the same scale). This leads to the conclusion that the source of the idea for the new product may not be a particularly strong discriminator between successes and failures. The same conclusion can be drawn about the relative magnitude of the firm's investment in the project.

Though this study offered the marketing literature the first real insight into managers' beliefs about the influence of different factors on new product success and failure, there are several limitations of the study which should be mentioned. First, three of the factors which entered Cooper's (1978) discriminant function consist of only two variables. **Market dynamism, Relative price of product**, and **Source of idea/investment magnitude**, all consist of two variables apiece. Operationalizing a scale using only two variables makes it impossible to determine the scale's reliability (Cronbach's alpha cannot be correctly calculated with only two variables). In fact, the author did not indicate the reliability of any of his scales; no assessments of scale reliabilities were included in the work.

Another problem is seen upon examining the factor analysis results. Many of the variables load on more than one factor, making the results less than "clean." This also indicates that many of the factors are conceptually related, which might indicate that there is significant collinearity between factors. If so, this collinearity may induce bias in the discriminant analysis since it may result in highly unstable structural coefficients (Dillon and Goldstein 1984).

Many other studies have used Cooper (1978) as a prototype for further work in this area. Table 4 shows the results of three other studies using variations of this methodology. Examination of their findings reveals similarities in results. Many of the factors discovered by Link (1987), Zirger and Maidique (1990) and Cooper and de Brentani (1991) are almost identical to the findings of Cooper's (1978) original study. For example, five of Link's (1987) six factors are almost identical to five of Cooper's (1978) factors, though they are not in the same order. Link's (1987) sixth factor, **Product quality**, appears at first glance to be unique; however, it is closely related to Cooper's (1978) first factor, **Product uniqueness/superiority.** In fact, in that study product quality loaded on this factor.

Zirger and Maidique (1990) likewise had very similar results to Cooper (1978) in their study of U.S. equipment manufacturers. Again, there were very few differences in the factors. The only real difference was that they found **Management support** to be positively related to new product success, whereas Cooper (1978) did not include variables relating to management support of the new product in his analysis.

The three studies discussed above were all performed on a sample of manufacturing firms. To assess whether factors influencing new product success/failure were dependent on the type of product being developed, Cooper and de Brentani (1991) investigated these issues using a sample of 37 firms in the financial services industry. They found very few differences. Managers believed that many of the factors influencing the success/failure of manufactured goods also influenced the success/failure of new financial services. The authors included several factors that were thought to be specifically relevant to the success/failure of services (e.g., degree of service customization, service intangibility, etc.). The only such factors to be relevant were **Service expertise** and **Quality of service delivery.** However, it can be argued that these factors are very related to factors listed in other studies, such as **Product quality** or **Product uniqueness/superiority** since they both have to do with the quality of the product or its superiority to competing services in meeting customer needs.

In summary, then, much work has been done to ascertain managers' beliefs about product success/failure. By and large, the different studies have reported very similar results. Many of the same factors are believed to be related to new product success/failure by managers in different industries, including the financial services industry. These factors are conceptually related to the factors which the normative literature suggests should be used in the evaluation of NPCs, lending support to the use of those criteria.

However, it is interesting to note that the rank ordering of the different criteria does change from study to study. For example, Cooper (1978) reported the most important discriminator between successful new products and those that had failed was the product's uniqueness and superiority. Zirger and Maidique (1990), however, report the most important discriminator to be the level of excellence of the firm's R & D organization and activities. This suggests that there may be dimensions which influence the relative importance of any specific factor on product success and/or failure. For example, industry effects may influence which factors are most important in determining whether a product will succeed or will fail. It is easiest to see that this may be the case if one contrasts the rank ordering of discriminating factors in the studies by Cooper and de Brentani (1991) and Link (1987) with those of Cooper (1978) and Zirger and Maidique (1990). In the latter pairing, technical and production performance or proficiency appear to be very strong discriminators between successful and unsuccessful products. However, in the former pairing, this factor is not found at all (Link 1987) or is related to factors farther down the list of discriminating factors. Apparently, technical skill and proficiency is an important discriminator between successful and unsuccessful products for both Canadian and US manufacturers of industrial products, but is relatively unimportant in the Australian industrial manufacturing industry or in industrial financial services.

Another interesting point to consider, and one that is particularly germane to this review, is that no researcher in this body of literature has acknowledged that it is the managers' *beliefs* about product success/failure that are really being researched here, not the products themselves. In fact, in his ground breaking study, Cooper (1978) reported as his sample for the study the *number of products* (both success and failures) that the managers reported on, not the managers themselves. In his later study with de Brentani (Cooper and de Brentani 1991), the *number of products* was again reported as the sample being studied. The majority of the other studies in the literature take the same point of view.

This is significant because it is easy to see that assuming that the product itself is the unit of analysis obscures what is actually taking place. It obscures the importance of *managerial perception* in the entire process of new product evaluation. It implies that researchers in this area do not appreciate that there may be many characteristics intrinsic to the respondent that determine which factors are deemed to be related to new product success/failure. For example, no author investigated the respondent's educational or functional background to determine if either influenced attributions of success or failure. It would be easy to imagine that a person who was trained in marketing or whose functional background was in marketing might be more inclined to say that marketing proficiency was more important to product success than was a person whose background was in manufacturing. Also, it is not clear how managers' beliefs about specific products become generalized in schema. Managers might have certain beliefs about what caused a specific new product to fail or to be successful, but these specific beliefs may not be held about all new products in general.

Though these studies provided important information into managers' beliefs about factors which influence product success and failure, researchers did not investigate how these beliefs influenced the decision maker's behavior. While it is important to understand managers' beliefs about new product concepts, it is also important to know how their beliefs influence their search for information as well as the subsequent decisions they make about these products. The study outlined in this proposal investigates some consequences of managers' beliefs for their information search behavior and their decisions.

Another factor which may influence managerial perception is the decision maker's level of experience. In the next section, I review literature on the effects of experience on decision making. In much of this literature, researchers implicitly assume that by gaining experience, a decision maker gains expertise. Therefore, I also review the literature on expertise effects on decision making. A review of this literature provides evidence that there are real differences in the knowledge structures of experienced and inexperienced decision makers. As yet, no work has been done to investigate these differences and their possible impact on the evaluation of new product concepts or attributions of product success/failure.

Effects of Experience/Expertise on Decision Making

A good working definition of an expert is one who possesses a good deal of both *procedural knowledge* as well as *declarative knowledge* about a particular decision domain (Hershey, Walsh, Read, and Chulef 1990; Szymanski and Churchill 1990). The key assumption underlying much of the work on expertise and decision making is that decision makers rely on already developed knowledge structures to supplement simplified means of processing information. These knowledge structures, called schema, are organized chunks of information about the world that aid individuals in categorization and other aspects of information-processing (Klayman and Schoemaker 1990). Schema can be thought of as subjective theories about how the world works. These theories are derived from generalizing across one's experiences with the world.

Most of the empirical work on expertise and decision making originated in the fields of cognitive psychology and artificial intelligence (AI), growing out of work done in the mid to late 1960s. A brief review of the work in these areas will be followed by a more thorough analysis of the work on expertise in the business literature.

Review of the Literature in Cognitive Psychology/AI: In the mid to late 1960s, research in AI and attempts to simulate human capabilities in chess playing had failed to construct programs that could outperform humans, even though computers were by then equipped with powerful search heuristics and essentially limitless search capabilities (Chi, Glaser, and Farr 1988). Investigations into chess playing, primarily by deGroot (1966), showed that one factor that distinguished weak from strong players was their ability to correctly reproduce complex patterns of chess positions after a few seconds of viewing. The empirical work on expertise, which began with deGroot's work contrasting chess masters and novices, was extended to other areas of knowledge. Much of this work indicates that experts (those familiar and experienced with a specific knowledge domain) and novices (those inexperienced or unfamiliar with that domain) have very different knowledge structures.

For example, in a study of expertise in physics problem solving, Chi, Glaser, and Rees (1982) found that experts possessed more elaborate schema than novices. When asked to solve physics problems, experts solved the problems more quickly and with fewer mistakes than did novices. When asked to sort several problems into groupings on the basis of how they would solve them, there were no significant differences in the number of categories experts and novices used nor were there any real differences in processing time. However, their results were qualitatively different in that novices seemed to be sorting on "surface structure" (similarities in key words or objects in the problems) while experts classified the problems by the major physics principles which governed the solution of the problem.

The fact that experts solved problems faster but were not any faster at categorization makes an important point. The underlying premise of the literature on expertise is not that experts are hypothesized to have superior cognitive skills or capacities. It is just that their more elaborate structure of knowledge about the relevant domain allows them to access information more quickly and facilitates other functions, such as the ability to discern which information is more relevant to problem-solving.

Several other studies illustrate that experts and novices also differ in the way information is processed. Expert computer programmers have better recall of relevant information due to differences in the organization of knowledge (McKeithan, Reitman, Rueter, and Hirtle 1981). Experts' recall of information is less biased and they focus more on inconsistencies in the stimulus material than do novices (Fiske, Kinder, and Larter 1983). Lurigio and Carroll (1985) reported that expert probation officers have more detailed and meaningful schema for probation cases than novices. In a study on expertise and education, Glaser (1982) suggested that experts store and retrieve information from long-term memory differently than novices. Experts' schema are larger in long-term memory and more easily accessed from short-term memory.

Review of the Work on Expertise in the Business Literature: Expertise has received a great deal of attention in the business-oriented disciplines. The bulk of this research is in the consumer behavior literature, but interest in the topic is spreading in management and in marketing.

The interest in expertise in consumer behavior is largely due to the large influence of cognitive psychology in this field. There are many studies on expertise in this field (see Alba and Hutchinson 1987 for a more comprehensive review). For the purposes of this proposal, the focus will be on literature having to do with differences between novices and experts in information search and use in making decisions, such as categorization and problem solving.

According to Alba and Hutchinson (1987) expertise is the ability to perform domain-related tasks successfully. Expertise may be considered a prime determinant of information search behavior because of the way it mediates one's ability to learn about the domain in question and the cost of doing so. Because comprehension is a function of knowledge, the authors also propose that expert consumers, with their more highly developed knowledge structures, are better equipped to understand the meaning of product information. Therefore, more knowledgeable consumers are more likely to search for new information prior to making a complex decision. These propositions are supported by Brucks (1985). In an investigation of product class knowledge (analogous in many respects to expertise) and information search behavior, Brucks (1985) found that product knowledge was positively related to the number of product attributes examined in a complex choice situation. She suggested that knowledge facilitated the asking of questions about the attributes of alternatives. Interestingly, there was a positive relationship between knowledge and external information search, indicating that when asked to evaluate products and make choices among them, knowledgeable consumers search for *more* information than do novices. To explain this, the author suggested that experts may seek a greater amount of information about particular product attributes simply because they are aware of the existence of those attributes.

In a study of consumer knowledge and its effects on strategies used to evaluate products and product information, Sujan (1985) found that evaluation processes are contingent upon consumers' prior knowledge and the match of information to this knowledge base. When product information was discrepant from category knowledge, experts produced more thoughts than when information matched category knowledge. Novices did not produce more (or fewer) thoughts depending upon the match or mismatch of information. This is consistent with the finding that experts focus more on inconsistencies in the stimulus material than do novices (Fiske, Kinder, and Larter 1983).

In the marketing management literature, only two studies dealing with the effects of expertise on decision making could be found. In the study previously discussed in the review of the literature on NPC evaluation, Perkins and Rao (1990) not only investigated managers' use of information and their evaluations of NPCs but the also the effects of expertise (which they operationalized as years of experience) on information use and evaluation. They found that when asked to determine whether a new product should be introduced, expert managers differed not only in their decisions but in what information was used to make the decision, the importance of different pieces of information, and in their evaluations of the information's usefulness. In general, experienced managers used more pieces of information than did inexperienced managers. There were no significant differences in the weightings of the "hard" data presented to the managers (Nielsen store audit data, diary panel data, consumer research), but there were differences on the "soft" data. Experienced managers weighted headquarters support more heavily than did inexperienced managers, while inexperienced managers weighted merchandiser word of mouth more heavily than did experienced managers. It is also interesting to note that, in general, experienced managers were more conservative in their decisions regarding new product introduction; they were less likely to introduce new products when all information variables were as expected.

Subjects were also asked to make similar judgments about a consumer promotion decision, which was hypothesized to be a much more routine decision for the managers than a new product introduction. The authors found that there were very few differences between experienced and inexperienced managers in these types of decisions, which supported their supposition that expertise effects would be more pronounced for less structured decisions.

In a study of salesperson effectiveness, it was found that successful and unsuccessful salespeople did not differ on the number of attributes they used to categorize prospects (Szymanski and Churchill 1990). However, they did differ on the weights they assigned certain attributes and the values they felt sales leads must have on certain attributes (i.e., cutoffs on those attributes) to belong to a certain category. Though this study was framed in terms of salesperson success, it is relevant to the expertise literature since it is logical to presume that expertise is related to success.

Several interesting studies in the management literature further highlight the differences between experts and novices. In a study investigating financial problem solving, Hershey, Walsh, Read, and Chulef (1990) asked expert financial planners and novices to decide if a hypothetical couple should invest in an Individual Retirement Account (an IRA). Before beginning the problem solving process, subjects were asked to indicate what pieces of information they would need to solve the problem. (However, they were not limited to these pieces of information and could ask for as much additional information as was needed when they actually solved the problem.) The authors found many differences between the two groups. Experts were much more goal-directed in the way they solved the problem, they completed the task using fewer steps, they looked at fewer pieces of information, took less than half as much time, and used higher level (more abstract) information than did novices. In contrast, the solution paths of novices were highly repetitive;

they often looked at the same piece of information several times while trying to make their decisions, often not realizing that they had already looked at the information before.

This result, that experts looked at fewer pieces of information than did novices, seems contrary to the findings by Brucks (1985) discussed earlier. As discussed below, this contradiction points out that there may be task effects, such as the existence of scripts, which moderate the relationship between expertise and information search. Scripts are a special type of schema which outline procedures for accomplishing some task. As such, they usually involve temporal or episodic information. The possession of such a script is of great importance in problem solving because it allows the solution to become automatic (Alba and Hutchinson 1987). Reduced cognitive effort is then needed to solve the problem. This may lead to shorter solution times as well as a more goal-directed search. While a script may have existed for Hershey, Walsh, Read, and Chulef's (1990) task, Brucks (1985) provided a more complex task, for which scripts may not have been relevant and for which experts' more complex schema for product evaluation induced increased search.

Finally, two very interesting studies by Isenberg (1986) and Bateman and Zeithaml (1989) contrasted the decision behavior of managers with that of students. Neither study was framed as an investigation of expertise effects on decision making. In general, students are such utter novices when it comes to making typical real-world business decisions that contrasting their decision making with that of managers may not be an adequate or legitimate test of expertise effects as they exist in business. However, they do provide interesting insights into the effects of expertise on decision making.

Isenberg (1986) had two small samples of general managers and students analyze a short business case in which the protagonist had decided to centralize certain aspects of the company's purchasing process but had met with resistance from employees in the purchasing department. They were instructed to develop an action plan to "solve" this problem. They were instructed to think aloud while reading and solving the case and their statements were recorded. Verbal protocol analysis exposed several differences between the managers and students. Specifically, managers began planning their responses to the problem much sooner in their analyses than did students. They reflected on the information in the case less, reasoned more from the case (made statements that indicated that they were aware of cause-effect relationships or that they were reasoning by analogy), and asked for less additional information than did the students.

In contrast to these findings, Bateman and Zeithaml (1989) found no difference between samples of managers and students in a study on reinvestment. In this study, subjects had to decide how much money to reinvest in two divisions of a fictitious firms. The independent variables manipulated were decision feedback (subjects were given either positive or negative feedback on the outcome of an initial investment decision), perceived organizational slack, which is the amount of available resources over that which is needed by the organization (high or low), and decision frame (perceptions of the acceptable risk were stated in terms of chances of success or chances of failure). They found for both managers and students the highest reinvestment occurred when a positive decision frame was coupled with either an initial failure, low perceived slack, or a combination of both. The pattern of reinvestment in other conditions were similar for both samples.

This finding would seem to imply that for at least this reinvestment decision, there were no appreciable differences between managers and students. However, since all that was reported was the outcome of the decision process, it may be that the process by which the decision was made did differ for the two groups though the outcomes did not.

To summarize, for most of the studies in the business literature cited here, real differences between experts and novices have been found (excluding the findings of Bateman and Zeithaml 1989). These include differences in:

> the amount and type of information searched or accessed when trying to make a decision (Brucks 1985; Hershey, Walsh, Read, and Chulef 1990; Isenberg 1986; Perkins and Rao 1990);

reactions to information inconsistent with category knowledge (Sujan 1985);

the importance or weights of different pieces of information used to make a decision (Perkins and Rao 1990; Szymanski and Churchill 1990);

their understanding of the information needed before problem solving begins (Hershey, Walsh, Read, and Chulef 1990).

In general, these findings are consistent with work in cognitive psychology and artificial intelligence (Chi, Glaser, and Farr 1988; Chi, Glaser, and Rees 1982; deGroot 1966; Fiske, Kinder, and Larter 1983; Glaser 1982; Lurigio and Carroll 1985; McKeithan, Reitman, Rueter, and Hirtle 1981). However, there are seeming inconsistencies across studies. For example, Brucks (1985) and Perkins and Rao (1990) found that expertise was positively related to information search, while Isenberg (1986) and Hershey, Walsh, Read, and Chulef (1990) found that experts examined fewer pieces of information. The answer to this contradiction might lie in the presence of a well-developed script for experts for the type of task performed. Within their study, Perkins and Rao (1990) had subjects perform routine and a non-routine decision tasks. They found that expertise effects were obtained in the non-routine task, but did not occur in the routine task. This suggests that there is a task effect, such that the amount of information search exhibited by experts may depend upon the type of task performed. For a non-routine, complex decision task, experts will search for **more** information than will novices; for a routine, simple decision, they will search for **less** information. This could explain the above inconsistencies if the tasks performed in Isenberg (986) and Hershey, Walsh, Read, and Chulef (1990) were routine for the experts. In the case of the latter study, it is easy to see that this might be the case. Deciding whether a couple should invest in an IRA should be a simple decision for an experienced financial planner. In the case of the former, without knowing the specifics of the case used as stimulus, it is impossible to say whether it could be perceived by the subjects as a simple or routine problem.

There are several conceptual difficulties with the construct of expertise which must be addressed. The first issue is the conceptual definition of expertise. Just what is an expert anyway? Alba and Hutchinson (1987) define expertise as the ability to perform domain-related tasks successfully. Operationalizing this definition in terms of complex decision making has proven to be difficult, however. Because of their complexity, it is difficult to imagine a strategic decision that is so straightforward that there exists one solution that is agreed upon by a vast majority of decision makers to be the "right" solution. And because the outcomes of strategic decisions are not known for some time (often years) after the decision is made and because the impact of those decisions on the organization may not be fully understood until much later, it is difficult to say with any certainty at the time the decision is made whether it was right or wrong, good or bad. In some applications (Isenberg 1986; Perkins and Rao 1990), experience has been used as an operationalization for expertise. This is problematic, however, because there is no reason to assume that two people who have worked in the same domain for equivalent amounts of time have attained the same levels of knowledge.

Much of the work from cognitive psychology (Chi, Glaser, and Farr 1988; Chi, Glaser, and Rees 1982) has used an objective measure of expertise in the form of tests. Though this has found application in the consumer behavior literature on product knowledge as well (Brucks 1985; Sujan 1985), it is difficult to imagine what kind of objective measure could be used to assess expertise in strategic decision making because there is usually no one "right" answer. Of course, subjective measures (peer, employer, or self-evaluations) could be used, but these might induce a great deal of error or unreliability in any empirical work since it would be difficult to know what, if any, biases were present and how to counteract them. For these reasons, I used several measures to try to tap the expertise construct. These measures included such variables as the decision maker's years of experience in the area of new product development, the number of new product decisions in which s/he was involved, the proportion of those decisions which were successful, supervisory evaluations, and self-evaluations. In the methodology section, I will more fully explain which variables were included and the reasoning behind their use.

Relevant Research on Decision Processes

In this section of the literature review, I will discuss literature relevant to the decision process. This will include literature on Feldman and Lynch's (1988) accessibility-diagnosticity theory, including its relation to Stigler's (1961) work on the economics of information. In addition, I review the literature having to do with diagnosticity and importance.

Accessibility-Diagnosticity Theory: The accessibility-diagnosticity (AD) theory (Feldman and Lynch 1988) was developed to try to explain the effects of measurement operations on revealed correlations among survey measures of belief, attitude, intention, and behavior. According to the authors, the likelihood that a subject's response to a measure of one construct will be used as a basis for a response to a subsequently measured construct depends on: (1) the perceived diagnosticity of the first judgment for the second; (2) the accessibility of the first judgment for the second; and (3) the accessibility of alternative inputs to the second judgment.

The perceived diagnosticity of the first judgment or decision for a second (later) one is the degree to which the respondent believes that the answer to the first question correctly identifies how the second should be answered. Since specific factors governing the perceived diagnosticity of a particular prior response will depend on the nature of the second question and the goals it engenders, one should not expect to be able to specify some set of determinants of diagnosticity common to all judgment and choice tasks.

The accessibility of the first judgment in memory is a function of: (1) the time since the most recent activation of that cognition; (2) the amount of interfering material encountered in the same general content domain; (3) elaboration and rehearsal of the original information; (4) characteristics of the information itself that determine the rate of decay in the respondent's ability to retrieve it (e.g., vividness); (5) motivation and processing goals at the time of initial encoding of the information; and (6) retrieval cues, whether internally generated by virtue of prior knowledge or externally provided by priming, or the similarity of contextual cues at encoding and retrieval.

The third factor affecting whether a prior cognition will be used for a subsequent input for a later related judgment, the accessibility of alternative inputs in memory, is inversely related to the memorability of alternative inputs. This is because the increased accessibility of an input produced by its elaboration reduces the likelihood that other inputs will be retrieved from memory because of output interference. However, inputs that are easily accessible but not deemed to be very diagnostic may be ignored when more diagnostic ones can be retrieved; if more diagnostic inputs cannot be retrieved, more accessible inputs will be used.

The authors developed this theory to draw together seemingly unrelated findings from several studies in the cognitive psychology and consumer behavior literatures. However, additional tests of the AD theory have been conducted and have been generally supportive of its hypotheses. Lynch, Marmorstein, and Weigold (1988) conducted two experiments to test the main tenets of the theory. In the first experiment, subjects were faced with a choice between two brands, one described to them on paper (the stimulus brand) and one on which they had previously been given attribute information in memory (the memory brand).

The authors hypothesized that when attribute information was easy to retrieve from memory (accessible), subjects would use this information to make their choice; when attribute information was difficult to retrieve, subjects would not recall the specific attributes but would recall their previously determined overall evaluation of the memory brand as an input to choice. The authors manipulated the accessibility of the attribute information in memory by interfering with its retrieval.

The results were analyzed to test the major hypotheses of the accessibility-diagnosticity theory as explained by Feldman and Lynch (1988). Results revealed that under low interference consumers relied upon specific attribute information about the memory brand, but their overall evaluations of it were used under conditions of high interference. These results support the hypothesis that the probability that a cognition is used as an input to choice is a positive function of its accessibility in memory. Moreover, the authors reported that subjects made very little attempt to retrieve and process attribute information when it was made inaccessible.

The authors also found that when consumers had attribute information accessible in memory (in the low interference condition), they used that information to make choices despite having already formed an overall evaluation of the product. They interpreted these results to support Feldman and Lynch's (1988) hypothesis that when consumers have multiple potential inputs to choice accessible in memory, they will use the relatively more diagnostic inputs (i.e., the attribute information). They argued that the fact that one had previously rated a product as good or bad is only mildly diagnostic of whether that product is better or worse than a newly seen stimulus product. It would seem that subjects believed that they are more likely to make a better choice if they compare the new alternative's attributes to those of the brand in memory.

Lynch, Marmorstein, and Weigold (1988) conducted a second experiment to more conclusively evaluate the role of diagnosticity in determining whether prior evaluations are used as a basis for choice. In this experiment, subjects who had formed a set of consistent evaluations of a brand (all good or all bad) were more likely to use these evaluations later in a choice than subjects whose evaluations of the brand had been mixed. The authors argue that more consistent evaluations of a brand are more diagnostic, which increased their use.

Though Lynch, Marmorstein, and Weigold (1988) interpreted the findings of these two experiments to support the basic hypotheses of the AD theory, a basic limitation of their work must be noted. In their study, the authors interpreted enhanced memory for information (attributes or prior evaluations) following choice as evidence that this information was used *to make* the choice. There was no direct evidence that this was indeed the case, however, since no inquiries were made of subjects as to exactly how they chose between the product alternatives. Enhanced memory might reflect only retrieval of the information and not its use in choice. Without access to the subject's thought processes, through such methods as verbal protocols during the choice task or retrospective reconstruction of the decision process, it is impossible to say with surety whether information in memory is being used.

Herr, Kardes, and Kim (1988) also tested hypotheses of the AD theory. Their work specifically investigated the effects of information vividness on persuasion. In their original explication of the theory, Feldman and Lynch (1988) stated that characteristics of the information, such as vividness, could increase its accessibility in memory. Herr, Kardes, and Kim (1988) found that more vivid (accessible) word-of-mouth (WOM) information did have a greater impact on product judgments relative to less vivid (accessible) printed information. However, whenever vividness was manipulated for very diagnostic information (either very negative information or a prior impression), this accessibility effect disappeared.

Thus Feldman and Lynch's (1988) AD theory has been supported. However, as noted previously, the work on this area to date has concerned *internal* information search (search in memory). We intend, in the current research, to apply the theory to external information search. In this context, the AD theory has some parallel in Stigler's (1961) work on the economics of information (EOI).

<u>Economics of Information</u>: In his work on the economics of information, Stigler (1961) proposed a framework to aid in understanding consumers' information search behavior. He proposed that buyers inform themselves about what is available in the marketplace only to the point where the marginal cost of gathering information equals or exceeds the marginal return. In this framework, lack of accessibility of information leads to higher marginal costs of information, while lack of diagnosticity of information leads to lower marginal return.

Though the EOI framework may also be useful in predicting information search behavior, we believe the use of Feldman and Lynch's (1988) AD theory is more appropriate to the current research because it predicts the likelihood of a piece of information being searched. Stigler's (1961) EOI framework predicts that all information with a marginal return greater than its marginal cost will be searched. The AD theory, however, goes a step further.

Diagnosticity and Importance: Another issue is the conceptual distinction between diagnosticity and importance. An attribute of a product concept is *important* to its success or failure in the marketplace to the extent that a change in that attribute leads to a change in its likelihood of success or failure. An attribute is *diagnostic* if the decision maker believes that the product concept's success or failure can be reliably predicted from the product's value on this attribute. To illustrate the difference between importance and diagnosticity, imagine that an individual is evaluating new product concepts in a certain industry in which quality is very important to a new product's success. Further assume that this individual believes firmly that the results of initial focus group interviews are highly predictive of success or failure. In this instance, the product's quality is *important* because any change in the product's quality causes a change in its likelihood of success or failure. The focus group results are *diagnostic*, but not important, because a change in focus group results (e.g., through hiring an inept moderator) does not itself *cause* a change in the product's likelihood of eventual success or failure, although it may affect the individual's prediction.

This distinction is worthy of note given that some previous research has found little convergence among importance measures, some of which involve search. There are many different approaches in the literature for assessing attribute importance. These include conjoint measurement techniques, direct ratings of importance, methods based on subjective probability models, information search measures using information display boards, open-ended elicitation techniques, and Thurstonian methods using pairs of attributes (Jaccard, Brinberg, and Ackerman 1986). In a study designed to evaluate the convergence of these six approaches, Jaccard, Brinberg, and Ackerman (1986) found relatively little agreement between methods across individuals. If importance and diagnosticity are considered equivalent, these results seem to contradict the model.

However, there is also some support in the literature for the contention that the diagnosticity of a piece of information does influence its use in decision making. In a study of the relationship between consumers' product preferences and estimates of the utility of a given product attribute, Sheluga, Jacoby, and Jaccard (1979) found that measures of attribute importance (obtained by conjoint analysis, estimates of the utility of the attributes, and estimates of attribute importance obtained by graded pair comparisons) were *not* strongly correlated with information search measures. However, the *subjective search importance* of an attribute was highly correlated with information search measures. Subjective search importance was operationalized as follows: after performing several choice tasks for two different products, subjects were asked to rank order *the value of the product attributes in helping to make their preference decisions*. This measure was significantly related to both the extent of search and the order of search.

The operationalization of subjective search importance as the subjective rank ordering of the value of the product attributes in helping to make their preference decisions in the above study is conceptually very close to the definition of diagnosticity. The high correlations between this measure and the information search measures seem supportive. However, the particular method used may have caused a confound. The measure of subjective search importance was taken *after* the information search took place. When asked to determine which information was most useful in making their preferences, subjects might have simply used their accessible memories of the search to make their judgments. In other words, the causality of the relationship might have been reversed: high use in search may have created high judgments of diagnosticity (search importance). My study was designed to provide a better measure of the relationship between diagnosticity and search by taking measures of diagnosticity *before* information search.

Hypotheses

The specific hypotheses which I will test are discussed below and are listed in Table 6. Figure 3 shows the model of new product concept evaluation developed in the Introduction annotated to show the relationships being tested.

A decision maker's attributions about the factors that influence new product success or failure should influence his/her perceptions of the diagnosticity of information about new product concepts. Attributions, according to Kelley (1972), derive from the individual's beliefs about cause-effect relationships among factors in the environment. In the context of the evaluation of new product concepts, these beliefs provide the basis for the determination of which factors cause success or failure. These attributions, then, should influence the decision maker's beliefs about the ability of different pieces of information to discriminate between good and bad concepts. For example, if a decision maker believes that products fail if they enter markets with a great deal of competition, knowing the number of competitors facing any new product would allow the decision maker to make some subjective estimate of the product's chances of failure.

Note that success and failure may be attributed to different factors. A good deal of research on causal attributions focuses on protecting one's esteem as the motivation for making causal attributions. For example, several studies in consumer behavior have found that there is a tendency to attribute good outcomes to one's self (an internal or dispositional cause) and bad outcomes to external or situational causes (Folkes 1988). There is evidence that this tendency also exists in corporations. Bettman and Weitz (1983) found that corporations, in their letters to shareholders, attributed unfavorable performance to more external, unstable, and uncontrollable causes than they did favorable performance.

Following this reasoning, I make the following hypothesis:

H1: Attributions of new product success/failure to some factor will increase the perceived diagnosticity of information about that factor.

Also discussed in the literature review was the accessibility-diagnosticity (AD) theory developed by Feldman and Lynch (1988), which hypothesizes that the perceived diagnosticity of a piece of information will influence its use in decision making. This hypothesis was supported by Lynch, Marmorstein, and Weigold

(1988) who found that subjects used diagnostic information but did not use nondiagnostic information in a choice task. Herr, Kardes, and Kim (1988) also found evidence to support this hypothesis. They found that diagnostic information was used by subjects in an evaluation task even when that information was less accessible in memory than was less diagnostic information. Sheluga, Jaccard, and Jacoby (1979) also found that individuals' estimates of the value of different product attributes in aiding them to make a preference decision were highly correlated with both degree of information search and order of information search. These arguments lead to the following hypotheses:

H2: The perceived diagnosticity of an item of information for success or failure will be positively related to the probability of the information being acquired and negatively related to the order of its acquisition.

The literature on expertise argues that experts and novices have different schema or knowledge structures. Experts' schema are more elaborate than novices' (Chi, Glaser, and Rees 1982). This difference in the content or structure of knowledge leads to differences between experts and novices in the decision making process. This hypothesis has been largely supported by empirical work in the area. Experts and novices have been found to differ in the amount and type of information searched when trying to make a decision (Brucks 1985; Hershey, Walsh, Read, and Chulef 1990; Isenberg 1986; Perkins and Rao 1990); the importance of different pieces of information used to make a decision (Perkins and Rao 1990; Szymanski and Churchill 1990); and their understanding of the information needed before problem solving begins (Hershey, Walsh, Read, and Chulef 1990).

Experts and novices also differ in their levels of *declarative* and *procedural* knowledge. Declarative knowledge consists of knowing which facts are important while procedural knowledge connotes an understanding of how those facts can be combined to produce a solution. Since experts and novices differ on these two types of knowledge, they should also differ in their beliefs about which factors are important in evaluating a new product concept as well as how those facts should be combined to come to a decision. Experts' more elaborate schema should allow them to make more attributions about new product success and failure.

Following the above discussion, I hypothesized the following relationships:

H3: The decision maker's level of experience will be positively related to the number of attributions made for new product success and failure.

H4: Experience will affect the specific attributions made for new product success and failure.

H5: Experience will affect the perceived diagnosticity of information for new product success and failure.

Because experts have more elaborate knowledge structures, they can make use of more information and more different types of information than can novices. Novices' more limited schema cannot incorporate as much information. Because novices and experts have different schema about product success and failure, they will consequently evaluate new product concepts differently. Experts should look at more pieces of information than will novices, which might mean that they will take longer than novices to come to evaluate a new product concept. However, experts' increased familiarity with the decision domain should make their search for information more goal-directed than novices, perhaps counteracting the time added by searching more items. In their study, Hershey, Walsh, Read, and Chulef (1990) found experts' problem solution to be more directed and efficient. They argued that the highly directed, goal-oriented search patterns of experts was evidence that experts had a script for problem solving which allowed them to be more efficient in their search. If so, and if it is true as I hypothesize that order of search is influenced by the perceived diagnosticity of information, then experts' order of search should be more consistent with their ratings of the perceived diagnosticity of information.

H6: Experience will be positively related to the number of items of information acquired during the evaluation of new product concepts.

H7: Experience will also be related to the consistency between the order of search for information and the perceived diagnosticity of information.

H8: Experience will be related to the specific choice of information items gathered during evaluation.

H9: Experience will be related to the amount of time spent in search.

Because experts are hypothesized to have more elaborate schema than are novices, they should be able to make use of more information and more different types of information than novices when choosing among new product concepts. For this reason, they should be more capable of making use of a demanding compensatory decision rule. Novices would be less likely to use a compensatory strategy because of their more limited ability to handle information.

H10: Experience will be negatively related to the use of cutoffs.

H11: Experience will be positively related to the value of the cutoffs used on different criteria.

Finally, due to their use of different information and the differences in the way they put this information together, novices and experts may make different evaluations about new product concepts.

H12: Experience will be related to the evaluations of new product concepts.

Summary

My intention in reviewing the above literature was to make the reader aware of the work that has been done in understanding strategic decision making. The studies included in this review shed light on managers' thinking about new product concepts and the criteria they use in their evaluation. However, there are still many gaps in our understanding of this process. An investigation of expertise and diagnosticity as determinants of information search and use should contribute a great deal to our understanding of the entire decision making process regarding new product concept evaluation. This study should give insight into which factors managers believe to be predictive of new product success or failure and how these beliefs affect their search for and use of evaluative criteria.

An understanding of the effects of expertise on the strategic decision making processes may have profound theoretical and practical implications. Theoretically, it may provide groundwork for understanding the effects of a host of other variables, such as time constraints, task characteristics, and the costs of information on the decision making process. Practically, if it is possible to ascertain the differences in experts' decision processes, it may one day be possible to impart this knowledge to novices, thereby speeding up their "learning curves." This may have important implications for the training of new managers in new product development and a variety of other real-world situations.

Though conducting research on strategic decision making is difficult, it is of vital importance both to practitioners and to academia. In order to understand what information managers need to make these decisions, we must first understand their beliefs and how those beliefs influence their search for and use of information. It is also necessary to better our understanding of the process so that we may develop more effective ways of influencing it. Few, if any, of the normative prescriptions about how these decisions should be made take into account the managerial decision making process and managers' limitations in information use. In order to develop decision aids that attempt to counteract these limitations, we must first understand what they are. The current research was intended as a first step toward this deeper understanding of the strategic decision making process. The following chapter outlines the design and methodology of this research.

Methodology

The model of the new product concept evaluation process shown in Figure 2 is very complex. For the purposes of the current research it was necessary to narrow the scope of the inquiry in order to ensure that the project was of manageable proportions. In addition, I felt it was necessary to make the survey instrument as short as possible so that practitioners, who were the sample for this study, were not discouraged from participating. For these reasons, I decided to narrow the scope of the study to focus on the relationships between experience, attributions of success and failure, information search, the specific choice of evaluative criteria, and the evaluation strategy used to process information. I did not investigate the effect of information accessibility on information search. As discussed previously, I also excluded any measurement of causal schema.

This chapter of the proposal will detail the methodology I used to investigate the relationships among the variables discussed above. In this section, I will discuss a pretest I conducted to evaluate the validity of some of the measures I subsequently used in the main study. I will then discuss the main study itself, including discussion of the respondents, the specific tasks that respondents perform, and the measures I used to test the hypotheses discussed in the literature review.

Construct Validation Study

Though it is preferable to have multiple measures of a construct under study, during pretest, respondents reported that they found the questionnaire extremely long even with only one measure of the diagnosticity construct. Therefore, I conducted a construct validation study before the main study. The objective of this study was to ensure that the one measure I intended to use for measuring diagnosticity had some reliability.

There are several different methods of testing reliability. These include the *test-retest method*, the *equivalent-forms method*, and the *method of internal consistency* (Rosenthal and Rosnow 1984). The test-retest method assesses reliability by measuring the correlation between data taken from the same test adminstered at different times. The equivalent-forms method assesses reliability by calculating the correlation between data from comparable but different forms of the same test. Finally, the method of internal consistency correlates components of the test with each other.

The construct validation study I conducted is a form of the equivalent-forms method. I asked respondents to rate the diagnosticity of differrent information using three different measures of the construct. To assess the reliability of the construct, I then calculated correlations between the three different measures.

Sample

The sample for the construct validation study was 35 upper level MBA students at a large state university. These students were solicited from an MBA level marketing strategy class. All students who participated in the study were entered into a drawing for $50.

Questionnaire

The questionnaire itself was a computer-interactive questionnaire constructed using Ci3. It contained multiple measures of the diagnosticity construct and demographic items. The text of the questionnaire is in the Appendix.

I did not tell respondents that the objective of the study was to determine the reliability of different measures of diagnosticity. Instead, they were told that the objective was to better understand the relevance of different types of information in evaluating new product concepts. They were instructed to imagine that they were employed in the new product development department of a company which produced OTC pharmaceuticals.

Measures of diagnosticity: I used three different measures of the diagnosticity construct:

Measure 1 used the question "How useful would the following piece of information about the product concept be in predicting whether the product will succeed or fail in the marketplace?" Answers were on a 9-point scale, with 1 being

"Not at all useful in predicting success or failure" and 9 being "Extremely useful in predicting success or failure."

Measure 2 asked "How much influence would the following piece of information have on your evaluation of the likely success or failure of the product concept?" Answers were on a 9-point scale, 1 being "No influence on the evaluation" and 9 being "A great deal of influence on the evaluation."

Measure 3 asked "If you were to compare product concepts likely to succeed with product concepts likely to fail, how similar or different are they likely to be on" (at this point, one of the information items appeared on the screen). Again, they were to respond on a 9-point scale, with 1 being "very likely to be similar" and 9 being "very likely to be different."

The different measures were presented in random order, so there were no order effects. In order to make a questionnaire of manageable length, I used only 20 of the 38 possible information items.

Demographics and other information: I included in the questionnaire questions about students educational background and work experience, in case any of these variables influenced their responses.

Results

Table 7 gives results of the construct validation study. These results are also shown graphically in Figure 4. Because I didn't want to make the questionnaire prohibitively long, I used a subset of 20 of the 38 possible information items chosen so as to maximize the variance of the diagnosticity ratings.

As the results show, respondents were very consistent in their ratings of the 20 different items using the three different measures. The three measures "track" very well; that is, respondents' ratings of the diagnosticity of the different information items seems to be relatively consistent regardless of which of the measures were used to measure them.

Table 8 shows the correlations between the three different measures of diagnosticity for each item. As shown in the table, the average correlation between measures 1 and 2 is 0.66, between measures 1 and 3 is 0.41, and between 2 and 3 is 0.42. The correlations between measures 1 and 2 were significant at the $p=0.05$ level for all 20 information items. Obviously, measures 1 and 2 are strongly related. Measure 3 was not as highly correlated with either of the other measures. Since I could only include one measure of diagnosticity in the final study, based on these results and limited discussions with some of the respondents for the construct validation study, I chose measure 1. Either measure 1 or measure 2 seemed very reliable. I was swayed to use measure 1 by conversations with respondents in the construct validation study, who told me that measure 1 seemed easier to understand and to answer.

In the next section, I will discuss the methodology employed for the main study, which was conducted after the construct validation study was complete.

Respondents

The respondents for this survey were 62 decision makers involved in NPD in industry. Most of the respondents came from the either the pharmaceutical industry or the computer software industry as shown in Table 10. I chose these two industries for several reasons. First, in both these industries there is a great deal of new product development activity--many new products are offered every year. This is important because it guarantees that there are people in each industry involved in new product development.

The software industry provides a pointed contrast to other industries used in many marketing studies, which often involve consumer packaged goods. Using another industry besides consumer packaged goods would make the findings more generalizable. I also felt that people working in the software industry might be receptive to the questionnaire being on a diskette and being driven by a computer program because it is a format with which they are used to working. Yet another reason for using this industry was that representatives of the Software Publishers Association were interested in the study and provided me with access to the directory of their membership. The Software Publishers Association is the principal trade association of the personal computer software industry. It has a membership of nearly 1,000 firms and includes firms that develop, publish and market software, as well as firms that provide services to the software industry (such as hardware manufacturers, advertising agencies, and market research firms).

The software and pharmaceutical industries also differ in ways that may affect the criteria for new product concept evaluation. For example, though technological change occurs in both industries, the speed of that change is much faster in the software industry than in the pharmaceutical industry. The rapid development of new hardware in the computer industries drives the rapid development of software. This should make the pace of new product development in the software industry much more rapid than that in the pharmaceutical industry. The two industries also differ in the degree of government regulation they face; the pharmaceutical industry is overseen by the FDA, whereas the companies in the software industry have more relative freedom from government regulation. These and other differences between the two industries enhance the generalizability of findings that occur across industries, and may suggest contingencies for the importance of various criteria if difference are found.

Contact Method

I used the following contact method to reach respondents. First, I obtained a directory of firms in each industry. I obtained the directory of the pharmaceutical industry from CorpTech Information Services, Inc., a company which collects data on many different industries. They provided me with information on 77 different pharmaceutical firms, including the firm's phone number and the names of its principals. As previously mentioned, the Software Publishers Association (SPA) provided me with its membership directory. Listings for each company in the SPA directory provided a brief description of the company's business activities, product information, number of employees, its phone number(s), and the names of its principals.

I began data collection by writing a letter to either the CEO or the marketing director of each firm. If the firm were large (over 75 employees), I addressed the letter to the marketing director; if it were small (less than 75 employees), I wrote to the CEO. The cutoff between large and small was arbitrary; my reasoning was that if the firm had more than 75 employees, the marketing director might be closer to product development activities and to those employees involved in product development than the CEO would.

The initial contact letter briefly explained the nature of the study, asked for the recipient's support, and alerted the recipient that I would call to discuss the study further. It also promised that any firm that participated would receive a summary of the results once the study was completed.

In my follow-up conversation with the company contact, I answered any questions about the study the recipient had and asked for his/her company's participation. If s/he agreed to participate, I asked for the name of *any and all* people in the firm who were involved in new product development and who had access to an IBM-compatible computer. This was to ensure that I got a people with different levels of experience in new product development.

Of the 77 pharmaceutical companies I contacted, 24 (31.2%) initially agreed to participate. Of these 24, 16 firms provided at least one respondent. The response rate in the pharmaceutical industry then was 20.8% of the original 77 companies and 66.7% of those companies which initially agreed to participate. Thirty-four individual responses were obtained from these sixteen firms.

I contacted a random sample of 124 firms in the microcomputer software industry. Of these, 32 companies (25.8%) originally agreed to participate in the study. Of these 32, 16 firms provided at least one respondent. The response rate in the software industry then was 12.9% of the original 124 companies and 50% of those companies which initially agreed to participate. Twenty-six individual responses were obtained from these sixteen firms.

The remaining four respondents cam from an attempt to generate a heterogeneous sample of new product development managers across a variety of industries by advertising in "Visions", the newsletter of the Product Development and Management Association (PDMA). This sample was too small to be interpretable, and so analysis of these respondents is not presented here.

The total response was 62 individual responses from 37 companies. This represents a response rate of 17.1% of the 217 companies initially contacted, and 61.7% of the 60 to whom diskettes were sent.

Survey Instrument

In order to reach as large a sample as possible while minimizing cost and time, I used a survey. Because I was interested in patterns of information search and use, it was not possible to use a more conventional paper and pencil survey instrument because it would not allow me to track the respondent's interaction with the information. To do this, I used Ci3, a software program developed by Sawtooth Software, Inc. Ci3 allowed me to develop interactive questionnaires. These questionnaires were copied onto computer disks and were mailed to the individuals whose names I obtained from my phone conversation with principals of the firms.

Ci3 also provided additional benefits. Its ability to randomize the presentation order of questions and of items of information within questions allowed me to ensure that order effects did not influence the results. Ci3's programming language also allowed me to customize the study for each individual respondent. I will discuss my use of these features more fully where appropriate.

I developed two different versions of the questionnaire, one for the pharmaceutical industry and one for the software industry. The questionnaires were basically the same, the only difference being the situations described were changed slightly to be consistent with the respondent's industry. For example, in one of the questions in the pharmaceutical industry questionnaire respondents were asked to imagine that they were evaluating a new product concept for a "new over-the-counter pharmaceutical product." In the corresponding question in the software industry questionnaire, respondents were asked to imagine that they were evaluating a new product concept for a "new software product."

The Appendix contains a paper copy of the questionnaire developed for the pharmaceutical industry. Some of the questions contain blanks or have missing information. This is because the questionnaire was truly interactive; the information that respondents saw in many of the questions depended on respondents' answers to preceding questions. (I will explain this more fully in my discussion of the constructs and measures.)

Stimuli

The tasks for this study consisted of several exercises in which respondents' primary tasks were to: (1) search for information about a hypothetical new product concept and evaluate that concept, (2) evaluate new product concepts for which no information search was necessary, and (3) rate the diagnosticity of different pieces of information they might receive about a new product concept, and other tasks. The stimuli for these tasks included descriptions of several hypothetical new product concepts and a list of different information items that a manager might receive about a new product concept. I constructed the stimuli and tasks used in the study during pretesting with the aid of the normative list of criteria in Table 1, informants in the OTC pharmaceutical industry, and an informant in the microcomputer software industry. Discussions with these individuals included the types of information managers might use in the evaluation of new product concepts and other aspects of the screening and development processes. I tried to make the stimuli as realistic as possible (given the artificiality of the evaluation being performed on a computer) and tried to ensure that the information used in the tasks was actually information that a manager might in fact be faced with when evaluating a new product concept in the relevant industries.

I began with a list of over 50 evaluative criteria developed in the normative literature (Tables 1 and 3) and factors found to be influential in the empirical literature (Table 4). Pretesting proved this list to be much too long (it took almost two hours for my pretest respondents to complete the questionnaire), so with the aid of managers in the OTC pharmaceutical industry, I shortened the list to 38 different pieces of information that might be used to evaluate a new product concept. In designing this list, I tried to be careful to include items that differed in their diagnosticity in order to ensure that I was not restricting the range of diagnosticity too greatly. Table 9 shows the final list of 38 information items used in the diagnosticity rating task and the information search tasks.

Procedure

Figure 5 shows the major tasks performed by the respondents and the order in which they were performed. Other questions not shown in the figure were included in the questionnaire to gather additional information about the respondent's firm, the new product development process within the firm, the use of financial criteria in evaluation, and the respondent's training and experience in new product development. These additional questions also served to distance related tasks or questions from each other so that respondents would not refer back in memory to their responses to previous questions to help them answer current questions. For example, there were several questions about the new product development process within the firm and the type of product the respondent's firm produced between the first measure of the respondent's perceived expertise and the second. In many places in the questionnaire, I also used the Ci3 software to prevent respondents from backing up in the questionnaire to look at previous responses.

Measures

Success Attribution Measure: To obtain measures of decision makers' attributions about the success and failure of NPCs, respondents performed two different tasks. Because their attributions about success might have unduly influenced their subsequent attributions about failure (or vice versa, depending on the order in which the questions are asked), I separated the success attribution task from the failure attribution task with questions unrelated to attributions (demographic measures).

To obtain success attributions, respondents were asked to respond to the following:

> Before we talk further about new product concepts, we'd like to know about your beliefs about why new products succeed in the marketplace.

What factors do you think make a new product a success? A successful new product is one that meets your company's goals, whatever those goals may be. The factors could relate to characteristics of the product, the market, the company, competition or any other area.

List all of the factors you can think of. When you are finished, press ENTER twice. Press F1 if you need help.

Failure Attribution Measure:

Respondents were asked to respond to the following:

Earlier, we asked you why new products succeed. Now we'd like to know about your beliefs about why new products fail.

What factors do you think make a new product fail? A failure is a product that does not meet your company's goals, whatever those goals may be. The factors could relate to characteristics of the product, the market, the company, competition or any other area.

List all of the factors you can think of. When you are finished, press ENTER twice. Press F1 if you need help.

Measures of Experience and Expertise: I used several measures of perceived expertise and experience in the questionnaire. Specifically, I used three measures of perceived expertise and three experience measures. The following questions were used to measure respondents' levels of perceived expertise:

Measure PKNOW1

Compared to others in your field, how much do you think you know about evaluating new product concepts? Enter your response based on the scale below.

Respondents were to answer this question using a 9-point scale, where 1 = one of the LEAST knowledgeable and 9 = one of the MOST knowledgeable.

Measure PKNOW2

How frequently do you seek advice from others when evaluating new product concepts?

1	Almost never seek advice
2	Occasionally seek advice
3	Frequently seek advice
4	Almost always seek advice

Measure PKNOW3

Please rate your degree of expertise in evaluating new product concepts compared to others in your field. Enter your response based on the scale below.

Respondents were to answer this question using a 9-point scale, where 1 = one of the LEAST expert and 9 = one of the MOST expert.

I gathered several measures of experience, both industry experience and specific experience with new product development. This distinction was made between general and specific experience because many researchers argue that expertise comes about through *domain-specific* experience, not general experience (Alba and Hutchinson 1987; Chi, Glaser, and Farr 1988; Hershey, Walsh, Read, and Chulef 1990).

I operationalized industry tenure as the number of years the respondent had worked in the industry. The specific question was:

Measure INDTENRE

How long have you worked in this industry?

_____ years

Specific experience in new product development was operationalized in two ways: (1) the number of years in which the respondent has been involved in new product development, and (2) the number of new product projects in which the respondent had a role in the evaluation of the new product concept. The specific questions were:

Measure NPDTEN
How long have you been involved in new product development?

_____ years

Measure NPDDECS

How many new product projects have you had a role in evaluating? (Give a rough estimate if the number is large.)

Diagnosticity Measures: Each respondent in the study was presented with the list of information items shown in Table 9, one item at a time, and was asked to respond to the following:

--------------------------------------**FIRST SCREEN**---------------------------------------

Now imagine that you are considering product concepts for a new over-the-counter drug. We will describe pieces of information that could be acquired about this potential new product. Please indicate for each item how useful that piece of information would be in predicting whether the product will succeed or fail. At any time, you may use the Escape key (ESC) to back up and review your answers.

We realize that there are many items. Evaluating new products in your industry can be very complex! We really appreciate your input.

--**SECOND SCREEN**------------------------------------

HOW USEFUL WOULD THE FOLLOWING PIECE OF INFORMATION ABOUT THE PRODUCT CONCEPT BE IN PREDICTING WHETHER THE PRODUCT WILL SUCCEED OR FAIL IN THE MARKETPLACE?

For the item below, use either the numbers at the top of your keyboard or the ones on the number pad to the right to show your response based on the scale below.

1	2	3	4	5	6	7	8	9
Not at all useful in predicting success or failure								Extremely useful in predicting success or failure

Ci3 allowed me to present the list of items in random order for each respondent, so there was no threat of order effects influencing respondent's ratings.

Demographic Measures: I also collected demographic information about the respondents in order to determine if any of these factors might exert influence evaluations about new product concepts or information search. The questionnaire included questions about the respondent's educational level, educational background, functional background, gender, and age.

Perceptual Measures: Finally, I collected some perceptual measures about the tasks and the structure of the questionnaire itself to determine if the tasks performed seemed sufficiently realistic to the respondents to encourage them to act as they would have in a real-life situation. This would also help me determine if respondents were sufficiently motivated by interest to give sufficient thought to the questions asked of them, and if there were any improvements in structure which would make the questionnaire better, more interesting or a more sensitive instrument to test these relationships. Respondents were asked to rate the meaningfulness of the questions and presented information on an 11 point scale. If the respondent's answer was below the midpoint of the scale, there were asked to explain in an open-ended question.

Search and Evaluation Tasks

Respondents performed several tasks to provide measures for the **Search characteristics**, **Chosen evaluative criteria**, and **Evaluation strategy**. The first task was a search and evaluation task. Respondents were allowed to request information about and then evaluate three new product concepts, one at a time. Information was available on a subset of the 38 NPD criteria for each concept. These available criteria are shown in Table 9. The second task was a concept evaluation task that presented the respondent with much more limited information (only 5 information items). In this task I presented respondents with the information for each concept (they did not have to request it). The final task was a direct measure of the decision maker's use of cutoffs. Each task is explained in more detail below. The information provided to respondents about the concept was customized in the following manner.

Calibration of Evaluative Criteria: One problem in sampling across companies and industries is that realistic ranges of product and market factors may vary. To ensure that the evaluation tasks presented respondents with realistic values for the different evaluative criteria, I asked the respondents to define realistic values for the different criteria used in later evaluation tasks. Respondents responded to the following questions:

> What annual growth rate, in percent change in sales volume, must a potential market experience for you to consider it to be a high growth market?
>
> How big does a potential market have to be for you to consider it a large market? (If less than $1 million, use a decimal value.)
>
> How high do entry costs have to be for you to consider them high?
> (Entry costs may include all costs associated with development, R&D, market research, initial marketing, etc.) (If less than $1million, use a decimal value.)

Obtaining such information on the different evaluative criteria for each respondent allowed me to customize later questions so that each respondent saw realistic stimuli. The Ci3 software allowed me to manipulate these values and insert them in subsequent questions. For example in describing a high growth market, instead of programming a constant, I had the software retrieve the respondent's answer to the question about market growth rate and display a value which was 1.25 times that amount. This produced a highly attractive growth market appropriate to that respondent's company. Likewise, if I wanted the annual growth rate to be undesirable, I had the software display a value which was 30% of the response to that question.

The values for more judgmental, less quantifiable attributes did not need such careful scaling. For example, an important criterion for evaluation suggested by the normative literature is the amount of management's experience with the product and market (see Table 1) . Management experience is difficult to scale in a precise way. For criteria such as these, I gave the respondent relative values, describing management's experience as moderate, extensive, or limited.

Decision Making Context: According to Ronkainen (1985), the criteria used to evaluate NPCs change through the different stages of the NPD process. To ensure that all decision makers were evaluating the concepts at the same point in the process, I gave them specific instructions to frame their decision. They were told to imagine that they were responsible for evaluating opportunities for new products being considered by their firm early in the new product development process. They were also told to assume that preliminary information about these new product concepts was available, but no specific decisions had been made about product design, etc. (This corresponds to the Urban, Hauser and Dholakia's (1987) opportunity identification stage, which precedes the design stage.) In order to ensure that they were not overly concerned about having their decision making evaluated as being right or wrong, I stressed that we were interested in their subjective judgments, which may differ from person to person.

Single Concept Evaluation and Search Task: From this task, I obtained measures of the time spent in search, which criteria were searched, the number of criteria searched, the order of search, the evaluation of the concept, and the perceived likelihood of the product concept's eventual success or failure.

I chose to present the respondents with three new product concepts in order to determine if the type of concept they saw influenced their search behavior. Concept 1 was a "good" concept, with predominantly good (favorable) values on the different attributes. Of the 38 possible pieces of information (see Table 9), 24 had favorable values, 1 had a bad value, and 13 had neutral values. Concept 2 was a "bad" concept, with predominantly bad (unfavorable) values on the attributes (4 favorable, 20 unfavorable, 14 neutral). Concept 3 was a "mixed" concept, with some good values and some bad values (20 favorable, 14 unfavorable, and 14 neutral). I considered presenting respondents with more than three concepts but found during pretest that respondents felt the time necessary to complete and evaluate each concept and to complete the rest of the survey was prohibitive.

The three product concepts were presented one at a time. For each concept, 15 information items were presented. (The entire list of 38 items was not presented due to the limitations of size of the computer screen. It was not possible to show all 38 items and their values on the screen.) The list of 15 items presented to each respondent varied by respondent. Which items were shown to the respondent depended upon his/her ratings of the diagnosticity of the 38 items. I constructed the list of 15 items to present the respondent with information that varied in diagnosticity. When possible, I chose five items that the respondent had previously rated highest in diagnosticity, five items s/he had rated lowest in diagnosticity, and five items of medium diagnosticity.

For each concept, I presented the respondent with the list of 15 information items. S/he could then choose to examine the concept's value on any or all of these items. The list of items was randomized to ensure there were no order effects. The following three screens show the specific instructions given to and questions asked of the respondent. The third screen shows a typical information screen as it might look after D and L had been requested; however, this is only hypothetical. As discussed previously, the specific list of information items shown to each respondent depended on his/her previous diagnosticity ratings of the 38 information items in Table 9.

--**FIRST SCREEN**--

Imagine that your company has been considering three new product concepts. These concepts are currently in the concept testing stage, but the time has now come to decide if each of these concepts should be advanced to the next stage of the new product development process.

-------------------------------------**SECOND SCREEN**---------------------------------------

Please review each concept and decide whether it would be most appropriate to send it on to the next stage of development or if the concept should be abandoned at this point. You do not need to move forward any particular number of concepts. You may abandon them all or send them all forward in development.

You will see one product concept at a time and make a decision about it. For each concept you evaluate, some information is available. You may use any or all of it. To see a particular piece of information, simply type in its corresponding letter. You may then choose another piece of information if you wish. When you decide whether to abandon or move this concept forward, press Z.

Please remember obtaining information is costly in time and money. Please look only at information you feel you need to make the decision.

--**THIRD SCREEN**--

Type in the letter corresponding to the item of information you would like to see. WHEN YOU HAVE OBTAINED ENOUGH INFORMATION TO MAKE YOUR DECISION, PRESS Z.

CONCEPT 1

A	Demand made on company's financial resources	
B	Whether consumers must change their methods of use	
C	Projected market share	
D	Colleague's opinions of the product	FAVORABLE
E	Level of seasonal/cyclical fluctuations in demand	
F	Whether product offers a meaningful advantage to users	
G	Number of other products in development	
H	Speed of change in technology in the product-market	
I	Market entry costs	
J	Whether competition is vulnerable	
K	Extent of changes needed in distribution system	
L	Likely effect on sales of existing products	NO EFFECT
M	Market size	
N	Source or product idea (internal or external)	
O	Number of major competitors	
Z	READY TO EVALUATE PRODUCT	

To obtain the concept's value on any particular information item, the respondent indicated that s/he wanted to look at it by typing in its corresponding letter. The value then appeared to the right of the selected item. It remained visible throughout the subsequent search. The respondent could look at as many or as few items of information as s/he desired. After gathering as much information about the concept as s/he wanted, the respondent was then asked to make his/her evaluation of the product. The exact question was:

Should this concept be sent on to the next stage of development?

1 YES
2 NO

To gauge the strength of respondents' evaluations of the new product concepts, respondents were then asked to answer the following:

How likely do you think it is that this new product concept will be a success or a failure? Move the cursor to the position on the scale that shows your response.

|---|---|

Very likely to fail	Equally likely to succeed or fail	Very likely to succeed

The above measure was a continuous one; that is, respondents could place their cursor at any place on the line.

Cutoff Task: This task measured decision makers' use of cutoffs on four variables: (1) market size, (2) market growth rate, (3) estimated time from concept approval to introduction, and (4) number of major competitors. In pretest, respondents rated these variables as being highly diagnostic.

Even though I was imposing a good deal of structure on this task, I still wanted to make the situation as realistic as possible. To do this, I first asked respondents whether they wanted to make a cutoff on each attribute. This should have allowed respondents who didn't normally make use of cutoffs the option to not do so. The specific instructions given to respondents for this task were:

---**FIRST SCREEN**---

Now, imagine that you are evaluating new product concepts for established OTC pharmaceutical markets. You have a staff who might aid you in the evaluation of these concepts. You have the option of evaluating all available new product concepts yourself or you can request that your staff screen the concepts using various criteria so that you need not bother evaluating concepts that have some very negative characteristic.

---------------------------------------**SECOND SCREEN**---

Suppose that your staff can screen these concepts on any of four different criteria:

Market size
Market growth rate
Estimated time from concept approval to introduction
Number of major competitors

First, tell us for each criterion whether you would want your staff to screen on it. If you do, we will then ask you how good a concept will have to be on that criterion to be passed on to you.

These two screens were followed by screens asking if the respondent wished to screen out concepts using the variables above. The following questions were asked for each:

Would you like to have your staff screen out any product concepts on the basis of **market size**?

1) YES
2) NO

If the respondent answered yes, the following question was asked:

How large would a market have to be to make it worth your while to look at the concept, rather than having your staff screen it out?

$ __________ million

Single concept evaluation task without search: The primary focus of the previously discussed single concept evaluation search task was to allow comparisons of less experienced and more experienced decision makers' information search processes, as well as to investigate relationships between perceived diagnosticity and information search. Another interesting question is whether less experienced and more experienced decision makers evaluate new product concepts similarly given the exact same information. In the single concept evaluation search task, less experienced and more experienced decision makers may differ in their evaluations because they were presented with different information (since the list of information items they saw were prepared separately for each individual), or because they have searched different information, as opposed to weighing it differently. This task, a single concept evaluation without search, was designed to discriminate between these two explanations.

In this task, I presented respondents with very limited information about two product concepts. The information items were: (1) market size, (2) cost of entry into the market, (3) product quality relative to competitive products, (4) upper management support for the product, and (5) management's experience with the product-market. These five variables represented an interesting mix of quantitative and qualitative information about a new product concept, which allowed me to test if experience was related to heavier reliance on quantitative or qualitative information.

Respondents did not have to request information, the concept's values on all attributes were displayed on the screen. This task yielded measures of the decision made about the concept given all information, and the likelihood of the product concept's eventual success or failure given all information. The decision maker was given the following instructions:

> Now we would like you to look at descriptions of new product concepts for an established OTC pharmaceutical market and tell us what you think of them. This time, you will have to search for information; several items of information about the product concept will be displayed. However, this information will be limited. Make your evaluation assuming that the product is acceptable on all other dimensions.

As before, each concept was shown individually, with the value for each attribute displayed. After taking as much time as necessary to examine the information, the decision maker will be asked to evaluate each concept using the same measures as before:

How likely do you think it is that this new product concept will be a success or a failure? Move the cursor to the position on the scale that shows your response.

```
|-----------------------------------------|------------------------------------------|
Very likely                          Equally                              Very likely
to fail                              likely to                            to succeed
                                                                          succeed or fail
```

In the next section, I will discuss my analysis of the data resulting from this questionnaire and the results of the hypotheses tests.

Analysis and Results

In this section, I will present the results of my analyses as well as a discussion of those results. I will present descriptive statistics first and will then move on to analyses and discussion of tests of hypotheses. The results discussed in this section are based on the 62 respondents in the pharmaceutical and software industries. As discussed previously, I excluded the four respondents from other industries from the analyses because their small number made any statistical analysis on this group meaningless.

Descriptive statistics

Table 10 shows basic descriptive statistics about the respondents. The total number of respondents for this study was 62, 34 (54.8%) from the pharmaceutical industry and 28 (45.2%) from the software industry. Sixty-one respondents (98.4%) had some experience in evaluating new product concepts; this experience was gained either in their current positions, their former positions or both. Many respondents had important roles in the evaluation of new product concepts within their firms: 17 (27.4%) reported being the primary decision maker; 32 (51.6%) gave major input about the decision to the primary decision maker, and 9 (14.5%) gave some input to the primary decision maker. Given these statistics, it seems that this sample is a valid one for studying the relationships under question since the respondents have had adequate experience in the evaluation of new product concepts.

In terms of their functional backgrounds, most respondents (40.3%) were in marketing while another large group (19.4%) were in research and development. A large group of respondents (21.0%) described their functional backgrounds as "other"; examination of their open-ended responses as to what their backgrounds were reveals that most of these individuals described their backgrounds as being in management.

Respondents came from a wide range of educational backgrounds. Most (46.8%) had business backgrounds, but many had backgrounds in the sciences: 11.3% came from computer science, and 9.7% came from the physical sciences.

The rest had backgrounds in engineering, liberal arts, math, or the social sciences. The respondents were in general very well educated: 14.5% had done some postgraduate work, while 43.6% had master's degrees and 9.7% had doctorates. Only 4.8% did not have at least a bachelor's degree.

Finally, the majority of respondents (75.8%) were male and most were between 31 and 50 years old (74.2%). Another 11.3% were between 51 and 60.

Attributions

In two separate open-ended questions, respondents were asked to state what factors they thought made a new product a success or a failure. These responses represent the respondents' "top-of-the-mind" determinations of factors which influence a product's eventual success or failure. The attributions elicited here would most likely be accessed when evaluating a new product concept's chances of success or failure.

I examined the responses and developed a coding scheme to code each individual's responses. The coding scheme was based on the list of 38 information items used in the study. Unfortunately, respondents answers were not limited to the 38 items on this list. Respondents' answers were extremely idiosyncratic. Because of this, my eventual coding scheme included 75 different responses. The final coding scheme is shown in Table 11.

Using this coding scheme, I coded respondents' answers to the open-ended success and failure attributions. After coding, I enlisted the aid of a marketing doctoral student who used the same coding scheme to code the responses. Comparing our efforts, we initially agreed on 62.1% of the responses. After discussion of our differences, we both recoded the responses on which we initially disagreed and improved our level of agreement to 75.3%. Though this level of inter-rater reliability is low, it would be difficult to improve on given the extreme of idiosyncracy of the responses and the large number of possible answers. Given this, I used my own coding of the responses instead of those done by the marketing doctoral student because of my superior familiarity with the study.

The mean number of attributions for success and for failure are shown in Table 12. The mean number of attributions for success by all respondents was 4.77 (std. dev. = 2.27). The number of success attributions ranged from a minimum of 1 to a maximum of 11 attributions. The mean number of attributions for failure was 5.13 (std. dev. = 3.00), ranging from a minimum of 1 to a maximum of 13. There was no significant difference between industries in the number of success attributions (pharmaceutical mean = 4.94 vs. software mean = 4.57; $t_{60} = 0.63$, $p = 0.53$). The same was true for attributions for failure (pharmaceutical mean = 5.65 vs. software mean = 4.50; $t_{60} = 1.51$, $p = 0.14$) and attributions overall (pharmaceutical mean = 10.59 vs. software mean = 9.07; $t_{60} = 1.34$, $p = 0.19$). A repeated measures t-test showed that the difference in the number of success attributions and the number of failure attributions was not significant (mean difference = -0.35, $t_{60} = -0.97$, $p = 0.34$).

Analyzing respondents' attributions will answer the following questions: (1) what are the most common attributions for new product success and failure? (2) what are the differences between respondents' schema for success and for failure? and (3) are there differences in attributions between respondents in different industries?

<u>Attributions for success</u>: Table 13 shows the attributions ranked by the percent of respondents listing them as a cause of success. As shown in the table, many of the factors were only mentioned by a few respondents. Only 12 of the 75 possible attributions were mentioned by more than 10% of the respondents. These 12 attributions and the percentage of respondents attributing product success are listed below.

1. 67.7% -the product's offering a meaningful advantage to users;
2. 32.3%-the level of the product's differentiation from competitors;
3. 24.2%-the level and/or adequacy of marketing support for the product;

   24.2%-the product's price;

5. 21.0%-the product's value or cost effectiveness (from the consumer's perspective);
6. 16.1%-how easy it is to use the product;
7. 14.5%-the timing of the product's entry into the market;

   14.5%-the product's ability to meet the company's financial goals;
8. 12.9%-the product's or company's image;
9. 11.3%-the product's making limited demands on the company's financial resources;

   11.3%-the product's ability to be protected in some way (such as with a patent).

Many of the most frequent attributions have to do with the characteristics of the product itself and/or the value offered the consumer by these characteristics. These include: **offering a meaningful advantage to consumers, the product's differentiation from competitors, the product's price, its value or cost effectiveness,** and **its ease of use.** Indeed, the only factor in the top five that was not a characteristic of the product itself was the **level and/or adequacy of marketing support for the product**, with 24.2% of the respondents making this attribution. So, decision makers attribute a product's success primarily to its own characteristics or price, in addition to marketing support for the product.

Many of the above factors are conceptually similar to Cooper's (1978) findings. In that study, new product success was attributed to such factors as product uniqueness/superiority, marketing proficiency, and the relative price of the product. Zirger and Maidique (1990) reported that the third most popular attribution for product success in their study was the product's value.

Interestingly, few respondents attributed product success to market-related factors, which ranked highly in Cooper's (1978) findings, as well as the findings of other studies on managers' attributions (Cooper and de Brentani 1991; Link 1987; Zirger and Maidique 1990). Only 8.1% of respondents attributed product success to **market size**, while 4.8% attributed success to **market growth rate.** Both of these factors ranked highly in other studies.

<u>Attributions for failure</u>: Table 14 lists the attributions ranked by the percent of respondents citing them as a cause of failure. Again, few of the 75 possible attributions were made by more than 10% of the respondents. The 14 factors which were elicited from more than 10% of the respondents are listed below.

1. 43.5%-inadequate marketing support for the product;
2. 38.7%-the product's inability to offer a meaningful advantage to users;
3. 25.8%-market research was inadequate;
4. 24.2%-the product's price;
5. 22.6%-lack of differentiation from competitors;
6. 19.4%-the product's making excessive demands on the company's resources (19.4%);
7. 17.7%-the company's new product development process;
   17.7%-the product's level of quality compared to the competition;
9. 16.1%-the timing of the product's entry into the market;
10. 14.5%-the product's being inconsistent with consumers' expectations of the product or the company;
    14.5%-taking too long to develop the product;
    14.5%-competitive retaliation against the product;
13. 11.3%-the distribution system for the product;
    11.3%-the number of major competitors the product faced.

As shown, the most prevalent attributions for product failure differ from those made for product success. As discussed above, many of the most frequent attributions made for a product's success had to do with the product itself. However, only four of the 14 attributions for product failure had to do with the product itself (**the product does not offer a meaningful advantage to users, the product's price, lack of product differentiation**, and **the product's quality compared to the competition**). Many of the other attributions made for failure had to do with the demand made on the company's capabilities or resources. Indeed, the most common attribution was the level and/or adequacy of marketing support for the product, with 43.5% of respondents ascribing product failure to a weakness in this area on the part of the company.

Interestingly, many of the factors to which respondents attributed failure were under the company's control. This seemingly contradicts the findings of many studies in consumer behavior which have found that there is a tendency to attribute good outcomes to one's self and bad outcomes to external causes (Folkes 1988). This also contradicts the findings of Bettman and Weitz (1983), who found that corporations attributed unfavorable performance to more external, uncontrollable causes in their letters to shareholders. In this study, respondents did acknowledge that the company might in fact be responsible for their product's failure.

Product quality did not rank highly as either a cause for product success or product failure. Only 6.5% of the respondents attributed success to a product's quality while 17.7% attributed failure to a lack of quality. This might imply that, at least in these decision makers' minds, quality does not have much impact on a product's outcome. However, another interpretation of this finding might be that most managers assume that a product will have comparable quality to its competitors and therefore do not think of it as a cause for product success or failure.

<u>Industry effects on attributions</u>: To test whether the respondent's industry had any effect on his/her attributions, I crosstabulated each success and failure attribution by industry. Table 15 shows the crosstabulations for all crosstabs that were significant at the $\alpha = 0.10$ level. As shown in the table, respondents differed in their tendency to attribute success to five factors and their tendency to attribute failure to seven factors. It must be noted that for many of these crosstabs, the X^2 test might not have been a valid test because the proportion of cells with expected frequencies less than 5 is greater than 20% (Ott 1988). It also should be noted

that none of the factors for which the crosstabs were significant are factors to which more than a few respondents attributed either success or failure.

Although lack of statistical power prevents conclusions about differences, some of the possible differences in success and failure attributions between industries seem plausible. For example, it makes sense that managers in the pharmaceutical industry would be more likely to attribute success to the ability to legally protect the product given that they might be able to protect a new drug formulation with a patent. A software developer's ability to protect his/her product, which is essentially an intellectual property, is extremely limited because it is very easy to copy software. Software developers would then be unlikely to see this as a realistic cause of success for their products. They would then be unlikely to see this as a realistic cause of success for their products. However, in general, no conclusions about industry differences are possible.

From the above discussion, it seems that the schema that managers possess about the factors that influence product success and failure can involve many different factors. These schema were very idiosyncratic; excepting "whether the product offers a meaningful advantage to users," even the most frequently cited factors were elicited for less than half of the respondents. It is also evident that the likelihood of attributing success to a factor differs from the likelihood of attributing failure to that factor. For example, 43.5% of respondents attributed a product's failure to the level and/or adequacy of marketing support. Though this factor was also important in terms of people's success attributions, only 24.2% attributed a product's success to this factor.

Diagnosticity ratings of the information items

Another measure of interest was the respondent's rating of the diagnosticity of the different pieces of information s/he might receive about a new product concept. In this section, I shall summarize respondents' ratings of the diagnosticity of the 38 information items with which they were presented. These items are listed in Table 9.

Having respondents rate the diagnosticity of a list of information items provides different information than the previous open-ended attribution task. Diagnosticity can be thought of as *predictive usefulness* of the information, while the attribution questions should have elicited factors which *caused* product success or failure. Note that some factors never elicited might be found to be diagnostic. Respondents' "top-of-the-mind" attributions might not indicate the true complexity of the schema they hold for success and failure.

Means: Table 16 shows the mean ratings of the diagnosticity of the 38 information items in Table 9 ranked from most to least diagnostic for all respondents. Figure 6 shows a graphical representation of the mean diagnosticity ratings for all of the information items. The item deemed to be most predictive of a product concept's chances for success or failure was whether it offered a meaningful advantage to users (mean diagnosticity rating = 8.2). Respondents also considered the level of the product's differentiation from its competitors (mean = 7.8) and its quality compared to the competition (mean = 7.8) to be very predictive of success or failure. The least diagnostic item of information was the source of the product idea (mean = 2.7). This is consistent with Cooper's (1978) study in which the source of the product idea did not weigh heavily in a function which discriminated product successes from failures. Interestingly, the level of upper management support for the product (mean diagnosticity rating = 7.5) was found to be more diagnostic than many other factors, including market growth rate (mean diagnosticity rating = 6.7) and whether the product could be legally protected in some way (mean diagnosticity rating = 6.3). Figure 6 shows that all but two items were rated above the scale's mid-point, indicating that most items were considered to be diagnostic.

To determine which of the mean diagnosticity ratings are statistically different from each other, I conducted a repeated measures t-test. Difference measures were tested for (38)(37)/2 = 703 pairs of ratings. To adjust for the large number of tests, I used a stricter criterion for significance using the Bonferroni procedure (see Rosenthal and Rosnow 1984), α = (0.10/703 =) 0.0001. For brevity, results of all these tests will not be presented here. Findings show, however, that mean differences between ratings of approximately 1.2 points are statistically significant. This means, for example, that whether the product offers a meaningful advantage to users, which has a mean diagnosticity rating of 8.2, is statistically greater than any factor was has a mean diagnosticity of 7.0 or less.

Using the above, some interesting comparisons can be drawn from the mean diagnosticity ratings. First, it is interesting to note that the level of upper management support (mean diagnosticity = 7.5) was rated as being more diagnostic than many other factors (those with diagnosticity ratings of 6.3 or less). This includes such factors as the concept's projected market share, the market growth rate, and many of the competitive factors (likelihood of new competitive entry into the market, strength of potential competitors not yet in the market, and the likelihood of competitive retaliation against the product). These latter factors are often mentioned in the normative literature on concept screening as being of great importance (see Table 1). The level of upper management support for the product is not often mentioned in this literature, which might indicate that the rational screening models advocated by this literature (for examples, see Busch and Houston 1985; Servi 1990; Urban and Hauser 1993) do not adequately take into account the political reality of concept screening inside many organizations. Upper management support was also valued more highly than consumers' evaluations of the product using focus groups (mean diagnosticity = 6.1).

Other interesting findings include that respondents seem to believe that salespeoples' opinions of the new product concept (mean diagnosticity = 6.6) are more indicative of its chances for success or failure than are their colleagues' opinions (mean diagnosticity = 5.2). The source of the product idea (mean diagnosticity = 2.7) was much less diagnostic than any other item.

<u>Factor analysis</u>: There was a great deal of intercorrelation among the diagnosticity ratings of the 38 information items. I attempted to factor analyze these ratings to find a lesser number of underlying constructs. However, the factor analysis was not successful. Principal components using SPSS Release 4.1

extracted 12 factors which accounted for 74.6% of the variance in the diagnosticity ratings. However, there was much overlap in the way ratings of the different items loaded on the factors. A varimax rotation of these factors did not converge, resulting in no clean and simple way to interpret the 12 factors. Though this is problematic, it is not unusual that the ratings of these information items should be so interrelated. All items relate to important marketing information which might be useful in evaluating a new product concept.

MANOVA: Since respondents came from two different industries, I ran a MANOVA on the ratings of all 38 items to see if there were industry differences on the ratings as a whole. (For a two-group test, this is equivalent to using Hotelling's T^2.) The results of this were not significant (Hotelling's $T^2 = 1.66$, $F=1.01$, $p = 0.51$). This indicates that respondents from the two industries did not differ in their ratings of the diagnosticity of the list of information items. This is not surprising, in that one would not expect managers to rely on a completely different set of factors in the two industries. However, since the power of this test to detect differences is presumably low (due to the small sample size and the large number of variables included in the MANOVA), I performed t-tests on the mean diagnosticity ratings for each of the 38 items.

T-tests: Table 17 lists the information items for which the t-tests on the mean ratings by respondents in the two industries were significant at the $\alpha = 0.10$ level. Though none are significant at the adjusted α of $(0.10/3 =)$ 0.003 level, these findings are important from a descriptive standpoint. As shown in the table, respondents in the two industries significantly differed in their ratings of 8 of the 38 items: (1) market growth rate, (2) whether costs drop with volume sold, (3) the level of seasonal/cyclical fluctuations in demand, (4) the likelihood of new competitive entry into the market, (5) salespeople's opinions of the product, (6) whether the product is patentable, (7) projected market share, and (8) the likelihood of adverse government regulation. For almost all items, respondents in the pharmaceutical industry rated the information as being more diagnostic than did respondents in the software industry. The only item which the software respondents rated as being more diagnostic was salespeople's opinion of the product. Respondents in the software industry rated this as being relatively highly diagnostic (mean rating = 7.32) while respondents in pharmaceutical did not value salespeople's opinions quite so highly (mean = 6.06).

In light of the fact that 38 t-tests were performed, we would expect 4 tests to show significant differences by chance compared to the 8 that were found. To adjust for the number of tests, a stricter criterion for significant of $\alpha =$ (0.10/38 =) 0.003. Using this adjusted level of significance, none of the above t-tests are significant. Thus, there is some ambiguity about how much reliance to place on the industry differences that emerged.

Another issue of interest is what is the perceived diagnosticity of different types of information? That is, if the 38 information items are classified into groups depending on whether they relate to the product, the market, or some other aspect of the situation, what would be the perceived diagnosticity of the different groupings? To investigate this issue, I classified each of the 38 information items into groups roughly based on the groupings shown in Table 1. Where items would not fit into this categorization, I created new categories, resulting in 11 categories in all. I then calculated the average diagnosticity of each group. These groupings, their average diagnosticity ratings and standard deviations are shown in Table 18. In the table, the groupings are ranked from most to least diagnostic. (Please note that the group numbers come from the numbers listed in Table 1. Where new groupings are created, they are given group numbers not listed in Table 1)

Table 18 also shows results of paired t-tests I conducted to determine which of the groupings actually differed in perceived diagnosticity. With 11 means, there are 55 possible pairs, so the adjusted level of significance for these t-tests is $\alpha =$ (0.10/55 =) 0.002. The results of the paired t-tests are shown in graphical form by ranking the means of the groupings from highest to lowest. All means not underlined by a common line are significantly different.

As shown in the table, the most diagnostic groups of items are **product factors**, with a mean perceived diagnosticity of 7.75, and **social/political factors**, with a mean perceived diagnosticity of 7.47. The paired t-test of these two group means was not significant (mean difference = 0.28, std. error = 0.26, t = 1.09, p = 0.28), indicating that the two groups of items do not differ in perceived diagnosticity. However, **product factors** are perceived as having higher diagnosticity than all of the other types of information, including the **match to organizational goals and capabilities** (mean diagnosticity = 6.84), which some authors have stated should be the most critical factor (Busch and Houston 1985). Interestingly, respondents did not perceive **market characteristics** as high as might have been expected (mean diagnosticity = 6.38). Information about the market for the new product concept was perceived as being less diagnostic than information about the **product, social/political factors**, and the **risk** the product might face.

By far, the least diagnostic piece of information was the **source of the product idea (internal or external)**, which had a mean diagnosticity of 2.74. Apparently managers in this study did not believe that ideas for new products that came from outside the company (such as from consumers, suppliers, or distributors) were any more likely to be successful than were ideas that came from within the company.

The **outcome of consumer research** about the new product concept, such as a focus group's evaluation and the results of quantitative analyses of consumer preference, received a mean rating of 6.52. This means that there was no significant difference between respondents' perceptions of the diagnosticity of consumer research and the **opinion of others** (colleagues and salespeople), which had the lowest perceived diagnosticity (mean diagnosticity = 5.90). If this is true, it would seem to imply that decision makers do not place a great deal of faith in the ability of consumer research to help them predict whether a product will succeed or fail. It might be useful for future research to delve further into managers' perceptions about the usefulness of consumer research to discover why they do not perceive it as being a very effective predictor of product outcomes and how it can be made more valuable to them in their decision making.

Expertise and experience variables

Means: Five of the measures of expertise and experience used were continuous variables. These were: perceived knowledge, perceived expertise, industry tenure, tenure in new product development, and the number of new product decisions in which the decision maker has been involved in over his/her career. Table 19 shows the means and standard deviations of these variables for all respondents as a whole and by industry. An examination of these means shows that respondents felt themselves to be very knowledgeable about new product concept evaluation compared to others in their field (mean = 6.11 on a 9-point scale) and they also felt that they were reasonably expert in new product concept evaluation (mean = 6.01 on a 9-point scale). Respondents had an average of 11.62 years of experience in their respective industries, with an average of 8.52 years being spent in new product development activity. The mean number of new product decisions in which they had been involved was 31.11.

One of the perceived expertise measures, the frequency of seeking advice, I used was categorical, not continuous. This variable measured how often the respondent asked others for advice when evaluating new product concepts. The frequencies for this variable are shown on the continuation of Table 19. Results show this to be a questionable discriminator between more and less experienced decision makers; almost all respondents (87.1%) said that they either frequently sought advice or almost always sought advice. Another 9.7% said they occasionally sought advice, while only 3.2% reported that they almost never sought advice.

MANOVA: To determine if there were any industry differences on the group of expertise and experience variables as a whole, I conducted a MANOVA on all the variables by industry. The results were not significant (Hotelling's $T^2 = 0.07$, $F=0.82$, $p = 0.54$). This indicates that respondents from the two industries did not differ in perceived expertise or experience. However, since the power of this test to detect differences is presumably low (due to the small sample size), I performed t-tests on the continuous expertise and experience measures (perceived knowledge, perceived expertise, industry tenure, tenure in new product development, number of new product decisions in which the respondent was involved). None of these t-tests were significant at the $\alpha = 0.10$ level, indicating that there were no significant differences in experience or expertise between the two groups of respondents.

Correlations: Table 20 shows the correlations among the expertise and experience measures. As shown in the table, perceived knowledge was highly correlated with perceived expertise ($r = 0.93$, $p = 0.0001$). It was also correlated significantly, but not as strongly, with tenure in NPD ($r = 0.24$, $p = 0.06$) and with the number of new product decisions with which the respondent was involved ($r = 0.36$, $p = 0.004$). The second expertise measure, the frequency of advice seeking, was not correlated with any expertise or experience measure. Perceived expertise was significantly correlated with perceived knowledge, with tenure in NPD ($r = 0.26$, $p = 0.04$) and with the number of new product decisions with which the respondent was involved ($r = 0.37$, $p = 0.003$).

The experience measures are all highly and significantly correlated with each other. Tenure in NPD was very strongly related to both the number of new product decisions ($r = 0.55$, $p = 0.0001$) and industry tenure ($r = 0.64$, $p = 0.0001$). The number of new product decisions was also strongly correlated to industry tenure ($r = 0.42$, $p = 0.0008$). Tenure in NPD and the number of new product decisions were both significantly, though not highly, correlated with both perceived knowledge and perceived expertise. However, neither was correlated with the frequency of seeking advice. Industry tenure was not correlated with any of the perceived expertise measures, which may be an indication that the measures are domain specific (only related to knowledge or experience in new product development, not overall industry experience). This indicates that they may be reasonable measures of expertise, which should be domain specific (Chi, Glaser, and Farr 1988).

Factor analysis: Because of the small sample size, I wanted to take every opportunity to decrease the number of variables in the analysis. To further this aim, I conducted a factor analysis of the six experience and expertise measures to determine if these measures were related to any underlying constructs. Principal components using SPSS Release 4.1 extracted 2 factors which accounted for 69.3% of the variance in the measures. Table 21 shows the factor loadings of the measures on the two factors. As can be seen in the table, all the experience measures (tenure in NPD, industry tenure, and the number of new product decisions) load on the first factor while all the perceived expertise measures (perceived knowledge, perceived expertise, and the frequency of seeking advice) load on the second factor. These results indicate these six variables may be represented by two factors, an EXPERTISE factor and an EXPERIENCE factor.

Reliability analysis: To determine if the six experience and expertise variables can be represented by the two factors discussed above, I conducted a reliability analysis using Cronbach's α. These results are shown in Table 22. Because the variables used different scales, I standardized the variables before conducting the analysis.

The results for the first factor, the EXPERTISE factor, show that with a value of 0.70 it meets the accepted cutoff for Cronbach's α of 0.70 for exploratory work (Churchill 1979). However, examining the item-to-total correlations shows that the second measure, the frequency of seeking advice, is not highly correlated with the other two measures ($r = 0.20$) and that Cronbach's α would increase from 0.70 to 0.96 if this item were dropped. This finding plus the fact that this measure was not correlated with any other expertise or experience measure and there was little variation in respondents' answers to this question, led me to decide that this measure should be dropped from any composite measure of expertise. Therefore, in further analyses using the construct of expertise, I will use a composite measure which will be the average of the respondents' ratings of their perceived knowledge and their perceived expertise.

Cronbach's α for the second factor, the EXPERIENCE factor, was 0.78, which exceeds Churchill's (1979) recommended minimum of 0.70 for exploratory work. An examination of the item-to-total correlations and the changes in α if each item were deleted shows that all three measures are highly correlated and that there would be no meaningful increases in α if any of the measures were deleted. Therefore, in further analyses using the experience construct, I will use a composite measure which will be the average of the respondents' standardized ratings of their tenure in NPD, the number of new product decisions in which they were involved, and their industry tenure. Standardization of the three variables is necessary because they are not measured using the same scale (tenure in new product development and industry tenure are measured in years, while the number of new product decisions is not).

Since these composite measures of expertise and experience are standardized, their mean is 0 and their standard deviation is 1. Below are the ranges for the two measures in the sample:

Composite measure	Minimum	Maximum
EXPERTISE	-2.74	1.59
EXPERIENCE	-0.91	4.01

The correlation between the composite experience and expertise measures is $r = 0.36$ ($p = 0.004$).

The next section presents results of the various tests performed to test the hypotheses listed in Table 6.

Tests of hypotheses

H1: Attributions of new product success/failure to some factor will be positively related to the perceived diagnosticity of information about that factor.

As discussed in the literature review, a decision maker's attributions about the factors that influence his/her perceptions of the diagnosticity of information about new product concepts. Attributions arise from the individual's beliefs about cause-effect relationships among factors in the environment, which should influence the decision maker's beliefs about the ability of different pieces of information to discriminate between good and bad concepts.

To test hypothesis H1, I conducted a repeated measures t-test to determine if respondents rated those items which were elicited in the open-ended attribution tasks as being more diagnostic than those factors which were not elicited. Separate analyses were conducted for success attributions and for failure attributions. Results are shown Table 23.

As shown in the table, this hypothesis was supported. For success, the mean diagnosticity rating of all items which were elicited was 7.72, while it was 6.61 for those items which were not elicited. The mean difference in diagnosticity was 1.11 (std. dev. = 1.26). This difference was significant (t_{57} = 6.76, p = 0.0001). For failure, those items to which failure was attributed had a mean diagnosticity of 7.77, while those to which no attributions were made had a mean diagnosticity of 6.59. The mean difference in diagnosticity was 1.17 (std. dev. = 1.16). This difference was significant (t_{55} = 7.59, p = 0.0001).

Two of the items, the level of seasonal/cyclical fluctuations in demand and the source of the product idea, were rated much lower in diagnosticity than all other items. To ensure that these two items were not unduly influencing the above hypothesis test, I again conducted the repeated measures t-test deleting these two items from the analysis. These results are shown in Table 23. Excluding these two items did not change the results. Items to which attributions were made were still rated higher than those to which attributions were not made. For success, the mean diagnosticity rating of all items which were elicited was 7.73, while it was 6.79 for those items which were not elicited. The mean difference in diagnosticity was 0.94 (std. dev. = 1.26). This difference was significant (t_{57} = 5.76, p = 0.0001). For failure, those items to which failure was attributed had a mean diagnosticity of 7.81, while those to which no attributions were made had a mean diagnosticity of 6.77. The mean difference in diagnosticity was 1.04 (std. dev. = 1.14). This difference was significant (t_{55} = 6.91, p = 0.0001).

Attributions of product success or failure to an information item were related to higher diagnosticity ratings of that item. As expected, managers' beliefs about the cause of product success and failure influence their beliefs about the predictive usefulness of information. This suggests that understanding managers' beliefs about the factors which cause new product success and failure could help us to better understand their beliefs about the usefulness of different types of information in decision making.

H2: The perceived diagnosticity of an item of information for success or failure will be positively related to the probability of the information being acquired and negatively related to the order of search.

Hypothesis H2 is based in the literature on the accessibility-diagnosticity (AD) theory developed by Feldman and Lynch (1988), which hypothesizes that the perceived diagnosticity of a piece of information will influence its use in decision making. This hypothesis was supported by Lynch, Marmorstein, and Weigold (1988) who found that subjects used diagnostic information but did not use nondiagnostic information in a choice task. Herr, Kardes, and Kim (1988) also found evidence to support this hypothesis. They found that diagnostic information was used by subjects in an evaluation task even when that information was less accessible in memory than was less diagnostic information. Sheluga, Jaccard, and Jacoby (1979) also found that individuals' estimates of the value of different product attributes in aiding them to make a preference decision were highly correlated with both degree of information search and order of information search.

Recall that respondents evaluated a series of three new product concepts, in which they had to specifically request items of information. To test the first part of hypothesis H2, that the likelihood of searching an item of information is related to its perceived diagnosticity, I created a variable called SELEC, which indicated whether a piece of information was selected by the respondent (SELEC is a binary variable). I then correlated SELEC with the diagnosticity ratings. I did this separately for each of the three concepts.

Before discussing the results of this test, I first present results on the mean number of items searched by the respondents. Table 24 shows the mean number of items selected for each concept. Recall that one concept was designed to have primarily good or favorable values for the attributes, one was designed to have primarily bad or unfavorable values, and one was designed to have evenly mixed (some good, some bad) values. (Also recall that the items presented to each respondent were dependent on his/her previous ratings of the diagnosticity of the different information items, so items presented to the respondents differed.) In general, respondents did not search very much of the information available to them. For the good concept, the average number of items searched was 6.90, or about 46% of the 15 pieces of information available. For the bad and mixed concepts, they searched an average of 5.47 (36%) and 6.15 (41%) items, respectively. Summing over all three concepts, they searched 18.2 pieces of information, or 40% of the 45 items available (15 items available for each of three concepts). A t-test on the number of items searched for each concept by industry revealed no significant differences, which leads to the conclusion that the respondent's industry did not influence how many items s/he searched.

Table 24 also shows results of repeated measures t-tests performed to determine if the number of items selected varied by decision context. Since three t-tests were performed, the results of these tests should be judged at an adjusted significance level of α = (0.10/3 =) 0.03. As shown in the table, respondents selected on average more information for the good concept than for either of the other concepts. The mean difference between the number of items selected for the good concept and the bad concept was 1.39, which was significant (t_{58} = 3.32, p = 0.002) and was a large effect (d = 0.87). The difference between the number of items selected for the mixed concept and the number selected for the good concept was -0.81, which was not significant (t_{58} = -1.97, p = 0.05). Neither was there any significant difference between the number of items searched for the bad concept and the mixed concept (mean difference = -0.56; t_{59} = -1.56, p = 0.12).

These results show that respondents put much more effort into investigating a seemingly good new product concept than investigating a bad one. If they found initial information about the new product concept to be favorable they searched further, perhaps looking for disconfirming evidence. This might reduce the riskiness of accepting a concept which initially looks good, but has some yet unseen flaw. However, when respondents found information to be unfavorable, they were unwilling to invest very much effort in searching for information. They felt more comfortable making a judgment about a seemingly bad concept with less information.

The results of the hypothesis test for H2 discussed above are shown in Table 25. As shown in the table, this part of the hypothesis was supported. The correlation between SELEC and diagnosticity was significant for all three decision contexts. For the good concept the correlation was 0.34 ($p = 0.0001$) while for the bad concept the correlation was 0.30 ($p = 0.0001$) and the mixed concept the correlation was 0.33 ($p = 0.0001$). This supports the hypothesis that whether a piece of information is searched is related to its diagnosticity.

The hypothesis was supported for all respondents, and for respondents in each industry when examined separately. As shown in the table, the correlations between SELEC and diagnosticity ratings were significant for pharmaceutical respondents and for software respondents.

To test the second part of hypothesis H2, that the order in which information is searched is related to its diagnosticity, I created another variable ORDER which contained the rank order in which a specific piece of information was searched. I gave any variables not chosen a rank order equal to the first rank not chosen. (For example, if 5 of the 15 pieces of information were chosen, then the 10 pieces of information NOT chosen were tied for rank order 6.) I then correlated ORDER with diagnosticity ratings. I did this separately for each of the three concepts.

Table 26 shows results of the correlation between ORDER and diagnosticity, which support this part of hypothesis H2. For all decision contexts, the correlation between the order in which a piece of information was searched and the diagnosticity rating of that piece of information was significant and negative. For the good concept, the correlation was -0.38 ($p = 0.0001$), while for the bad concept the correlation was -0.27 ($p = 0.0001$) and for the mixed concept the correlation was -0.35 ($p = 0.0001$).

Regardless of decision context, the order in which a piece of information was searched was significantly and negatively related to its diagnosticity rating. The higher the diagnosticity rating of a piece of information, the sooner it was searched. This implies that decision makers' search for information is governed by their beliefs about the predictive usefulness of that information.

H3: The decision maker's level of experience will be positively related to the number of attributions made for new product success and failure.

The literature on the differences between experts and novices argues that experts have more elaborate schema than novices (Chi, Glaser, and Rees 1982). If so, experts or more experienced decision makers should be able to make more attributions for product success and failure than less expert or experienced managers.

To test this hypothesis, I correlated the number of attributions made with the composite measures of the respondent's experience and expertise. These correlations are shown in Table 27. As shown, there is no relationship between experience or expertise and the number of attributions made for product success or product failure. Nor was there any relationship between the total number of attributions made and these measures. Thus, hypothesis H3 is not supported.

There are several reasons why these results might have been obtained. One explanation could be that more experienced or more expert decision makers' causal schema for product success and failure may <u>not</u> be more elaborate than those of their less experienced or less expert counterparts. However, another explanation may be that respondents felt significant time pressure when completing the questionnaire, and so limited the number of attributions they made to save time.

Although schema complexity should affect the number of attributions, the simple measure used here may have been inadequate to extract all attributions.

H4: Experience will affect the attributions made for new product success and failure.

Because more experienced and less experienced decision makers have different schema concerning product success and failure, the specific attributions made should differ for more and less experienced decision makers.

To test this hypothesis, I used logistic regression to determine if the respondent's experience and expertise were related to whether an attribution had been made. I first performed the regression over all attributions (as opposed to having 75 different regression equations) since this would provide a way of telling if experience and expertise were influential over the whole process of making attributions, then I performed a logistic regression on each attribution individually. (This is conceptually similar to performing a MANOVA on a list of variables, then performing an ANOVA on the individual variables to see which of the variables contributed to the significance of the MANOVA.)

Results of these regressions over all attributions are shown in Table 28. The table shows the standardized parameter estimates for the independent variables, the -2 Log Likelihood estimate, and the p-value for each regression equation. [The -2 Log Likelihood estimate gives a test for the joint significance of explanatory variables. See *SAS Technical Report P-200 , SAS/STAT Software: CALIS and LOGISTIC Procedures, Release 6.04*, (SAS Institute, Inc. 1990).] As shown in the table, neither regression equation was significant, indicating that neither experience nor expertise are significantly related to the attributions made by respondents.

The above result indicates that overall, neither experience nor expertise had an affect on the set of attributions made. To determine if experience or expertise affected whether a <u>specific</u> attribution were made, I also used logistic regression. The model for the regression took the form:

$$ATTRIB_i = \beta_0 + \beta_1 * EXPERIENCE + \beta_2 * EXPERTISE$$

where $ATTRIB_i$ = whether or not $attribution_i$ was made (i = 1 to 75 for the 75 possible attributions)
EXPERTISE = the composite measure of the respondent's expertise
EXPERIENCE = the composite measure of the respondent's experience.

Because there were 75 different attributions which could be made for both success and for failure, there were a total of 150 different regressions. Accordingly, an adjusted level of significance of $\alpha = (0.10/150 =) \ 0.001$ was used. None of the regressions were significant at this level, indicating that neither expertise nor experience had an effect on whether success or failure was attributed to a specific cause. Hypothesis H4 is not supported.

Though these findings do suggest that neither expertise nor experience are related to the attributions made for a product's success or failure, there may be other explanations. First, as discussed above, the simple attribution measure used in this study may have been inadequate to extract all of the respondents' attributions. This limited set of attributions may be inadequate to find existing differences between more and less experienced or expert decision makers. Another problem may be due to the small sample size, which may have severely limited the power to detect meaningful differences. Though I found no sources which would allow me to calculate the power of a logistic regression, it is likely that the power was very low due to the small sample size.

H5: Experience will affect the perceived diagnosticity of information for new product success and failure.

Experts and novices differ in their levels of *declarative* and *procedural* knowledge. Declarative knowledge consists of knowing which facts are important while procedural knowledge connotes an understanding of how those facts can be combined to produce a solution. Since experts and novices differ on these two types of knowledge, they should also differ in their beliefs about which factors are important in evaluating a new product concept as well as how those facts should be combined to come to a decision.

To test this hypothesis, I correlated the diagnosticity ratings of the 38 information items with the standardized composite measures of experience and expertise. Table 29 shows these results.

In light of the fact that 38 t-tests were performed, some of the correlations significant at the $\alpha = 0.10$ level may have come about through chance. To minimize this chance, a stricter criterion for significance would be $\alpha = (0.10/38 =)$ 0.003. Using this adjusted level of significance, none of the correlations are significant. This could mean that there is no statistically meaningful correlation between the ratings of the diagnosticity of the information and the decision maker's experience or expertise. There could be other reasons for the lack of support for this hypothesis, the most obvious of which is that the sample size is so small that it does not allow for an adequate test of this hypothesis. Despite this, it may be instructive to examine the findings more closely because they might provide descriptive insight about how managers' beliefs change as they gain expertise or experience. However, any discussion of findings is only meant to be informative from a descriptive standpoint.

The diagnosticity ratings of seven information items are correlated with expertise at the $p \leq 0.10$ level. These are:

(1) the demand made on the company's financial resources ($r = -0.24$, $p = 0.06$)

(2) whether the company can use current production processes ($r = -0.27$, $p = 0.03$)

(3) the level of seasonal or cyclical fluctuations in demand ($r = -0.55$, $p = 0.08$)

(4) the strength of potential competitors not yet in the market ($r = -0.24$, $p = 0.06$)

(5) the product's quality compared to the competition ($r = 0.35$, $p = 0.005$)

(6) a focus group's evaluation of the concept ($r = -0.31$, $p = 0.01$)

(7) the number of other products in development ($r = -0.33$, p 0.009)

For six of the seven information items, the correlation between the diagnosticity rating and expertise is negative, indicating that as expertise increases the diagnosticity of the information decreases. However, for the seventh item (the product's quality compared to the competition), the correlation is positive. Therefore, as expertise increases, the comparative quality of the product becomes more predictive of its future success or failure.

The diagnosticity ratings of three information items are correlated with experience at the $p \leq 0.10$ level. These are:

(1) the extent of the company's experience with the necessary technology ($r = 0.29$, $p = 0.02$)

(2) whether existing supply channels can be used ($r = 0.25$, $p = 0.05$)

(3) the likelihood of adverse government regulation ($r = 0.24$, $p = 0.06$)

For all items, the correlation between the diagnosticity rating and the composite experience measure is positive, indicating that as experience increases the diagnosticity of the information decreases. More experienced decision makers regard these pieces of information as being more predictive of a concept's future success or failure than do less experienced managers. It is interesting to note that two of these items deal with the product's fit with the company's current experience or capabilities. This suggests that as decision makers gain experience, they find information about the concept's fit with the company's current experience or resources to be more predictive of its future than they once did. Interestingly, neither information about the competition nor information about the market becomes more predictive as one gains experience.

The above relationships, while interesting, are not statistically significant. Therefore, hypothesis H5 is not supported. A possible reason for this lack of support would be the lack of power to detect statistically significant relationships if they did occur. For example, according to Cohen (1988) the power to find a correlation of 0.25 (approximately the magnitude of most of the correlations above) with a sample size of 60 using $\alpha = 0.10$ is about 0.60. The power to detect this correlation with a sample size of 60 using $\alpha = 0.01$(the lowest α level provided in Cohen's (1988) power tables) is about 0.28. This level is much lower than the more conventionally used 0.80 (Cohen 1988).

H6: Experience will be positively related to the number of items of information acquired during the evaluation of new product concepts.

Because experts have more elaborate knowledge structures, they can make use of more information and more different types of information than can novices. Novices' more limited schema cannot incorporate as much information. Therefore, as expertise or experience increases, the number of items of information searched should increase.

The mean number of items searched for each hypothesis are shown in Table 24. To test hypothesis H6, I correlated the number of items searched for each new product concept with the composite measures of experience and expertise. Table 30 shows these correlations and their significance levels.

As shown in Table 30, hypothesis H6 was not supported. The number of items searched was negatively and significantly correlated with expertise for both the good concept and the mixed concept, which is opposite of the hypothesized relationship. The correlation was also significant for the number of items searched over all three concepts. For the good concept, the correlation was -0.22 ($p = 0.08$), while for the mixed concept it was -0.24 ($p = 0.06$). The correlation between the total number of items searched over all three concepts and expertise was -0.24 ($p = 0.06$). Therefore, for both concepts, as expertise increased, the number of items searched decreased. More expert managers searched <u>less</u> than did their less expert counterparts.

Interestingly, this did not hold true for the bad concept. For this concept, which had fewer items searched, there was no relationship between the number of items searched and expertise (r = -0.17, p = 0.20). So, unfavorable information caused both more and less expert decision makers to terminate their search earlier. The significant and negative correlation between the total number of items searched over all three concepts and expertise indicates that, in general, as expertise increases managers are more comfortable making decisions with less information.

The results for experience show a similar pattern to those described above. The number of items searched is significantly and negatively correlated with experience for the good and the mixed concepts, but not for the bad concept. For the good concept, the correlation was -0.22 (p = 0.09), while for the bad and mixed concepts it was -0.08 (p = 0.56) and -0.26 (p = 0.04), respectively. As experience increases, information search decreases, at least when the information is favorable or is mixed. However, when information about the concept is unfavorable, search is more limited and experience has no effect on the number of items searched.

H7: Experience will be related to the consistency between the order of search for information and the perceived diagnosticity of information.

Experts' increased familiarity with the decision domain should make their search for information more goal-directed than novices. In their study, Hershey, Walsh, Read, and Chulef (1990) found experts' problem solution to be more directed and efficient. They argued that the highly directed, goal-oriented search patterns of experts was evidence that experts had a script for problem solving which allowed them to be more efficient in their search. If so, then experts' order of search should be more consistent with their ratings of the perceived diagnosticity of information.

This hypothesis amounts to saying that there is a significant interaction between experience and diagnosticity when looking at the order of search. To test this, I used regression analysis to analyze the following model:

where ORDER = the order of search calculated for each item selected (see discussion related to hypothesis H2)

$$ORDER=\beta_0+\beta_1*DIAG+\beta_2*EXPERTISE+\beta_3*EXPERIENCE+\beta_4*(DIAG*EXPERTISE)+\beta_5*(DIAG*EXPERIENCE)$$

EXPERTISE = the respondent's level of expertise

EXPERIENCE = the respondent's level of experience

DIAG*EXPERTISE = the interaction between the respondent's level of expertise and his/her diagnosticity ratings of the information

DIAG*EXPERIENCE = the interaction between the respondent's level of experience and his/her diagnosticity ratings of the information

Results of this regression are shown in Table 31. The regression was significant ($F_{2,864}$ = 29.58, p = 0.0001, R^2 = 0.15). As shown in the table, the interaction between expertise and diagnosticity was significant (t = 1.69, p = 0.09) but the interaction between experience and diagnosticity was not (t = -0.58, p = 0.56). This implies that the relationship between order of search and diagnosticity varies depending on the respondent's expertise, but not his/her experience. Examining the standardized parameter estimates shows that the interaction between expertise and diagnosticity (β = 0.19) has much less of an effect on the order of search than does the main effect of diagnosticity (β = - 0.39).

To determine how the order of search and diagnosticity are related depending on expertise, I divided the sample into two groups of roughly equal size by expertise and correlated the order in which an item was searched with its diagnosticity (using the same analysis I used to test hypothesis H2). The low expertise group had standard expertise levels less than or equal to 0, while the high expertise group had levels of expertise greater than 0. I tested the relationship between diagnosticity and order of search separately for each of the three concepts which the respondents evaluated. The results of this analysis are shown in Table 32.

As shown in the table, the correlations between order and diagnosticity did differ between low and high expertise groups for each of the three concepts. However, the differences were very modest and in all cases corresponded to very small effects. In all cases, the effect size, q, was less than 0.10 which is very small (Cohen 1988).

Table 32 also shows the same analysis for experience. Again, the two groups were divided on the basis of experience to provide roughly equal groups. The low experience group had standardized experience levels of less than -0.35 while the high experience group had standardized experience levels of greater than or equal to -0.35. As can be seen from the table, the correlations do differ between the two groups. However, the differences are again very modest and in all cases correspond to very small effects ($q < 0.10$; Cohen 1988).

H8: Experience will affect the specific choice of information items gathered during evaluation.

Because novices and experts have different schema about product success and failure, they will subsequently rate the predictive value of different pieces of information differently. Since their information search should be guided by their beliefs about the predictive usefulness of different information , more experienced and less experienced decision makers should search for different information.

To determine if experience or expertise were influential in the selection of a specific item of information, I used logistic regression. I regressed the selection of each item of information on the respondent's expertise and experience. I also included the respondent's industry as an independent variable, to determine if the selection of information was influenced by the respondent's industry. The model for these regressions was:

$$SELEC_i = \beta_0 + \beta_1 * EXPERTISE + \beta_2 * EXPERIENCE + \beta_3 * INDUSTRY$$

where $SELEC_i$ = whether or not information item i was searched (see Table 9 for a list of information items)
EXPERTISE = respondent's level of expertise
EXPERIENCE = respondent's level of experience
INDUSTRY = respondent's industry

Three separate regressions were run, one for each of the three new product concepts. Again, since each respondent saw a different list of 15 information items, respondents could not choose to search all 38 information items. If the respondent's list of items did not include a certain information item, SELEC was missing for that item. Only respondents who could have searched an item (the item appeared on their list) were included in each analysis.

The results of this regression for the good concept are shown in Table 33. Using an adjusted significance level of α = (0.10/38 =) 0.003, the only item for which the regression was significant was the likelihood of new competitive entry into the market (-2 log likelihood X^2 = 15.45, p = 0.002). Of the 16 respondents who had a chance to search this item, 6 (37.5%) searched the item while 10 (62.5%) did not. The standardized parameter estimates for this regression are shown below:

Variable	Standardized Parameter Estimate	Wald X^2	p	Odds Ratio
Expertise	-1.59	2.01	0.16	0.06
Experience	12.58	2.30	0.13	999.00
Industry	0.01	0.00	0.99	1.04

As shown in the above table, none of the parameter estimates are significant by themselves. However, examining the above estimates is still warranted since the combination of effects is significant at the p = 0.002 level. Since the parameter estimate for expertise is negative, this implies that as expertise increased, the likelihood of searching for information on the likelihood of new competitive entry decreased. The odds ratio shows that this decrease was dramatic. With each unit increase in expertise, the likelihood of searching this information item decreased by 94%. Experience had the opposite effect; as experience increased, the likelihood of searching this item increased tremendously. For each unit increase in the standardized measure of experience, the likelihood of searching this item increased by almost 1000 times. The parameter estimate for experience is almost eight times larger than that for expertise, so it is obvious that experience has a much larger effect on searching this information item than does expertise. The respondent's industry had virtually no effect.

Table 34 shows the results of the logistic regressions for the bad concept. None of these regressions was significant at the adjusted significance level of α = 0.003. So, for when information is bad, neither expertise, experience, nor industry had any influence on the likelihood of searching specific information.

Table 35 shows the results for the mixed concept. As shown in the table, the regression was significant for only one item, the ability to use the existing salesforce. The standardized parameter estimates for this regression are shown below:

Variable	Standardized Parameter Estimate	Wald X^2	p	Odds Ratio
Expertise	-0.32	0.57	0.45	0.60
Experience	1.26	1.39	0.24	28.27
Industry	-0.97	5.52	0.02	0.03

As shown above, neither expertise nor experience had any effect on the choice to search this information item. However, the respondent's industry had a great deal of influence. The parameter estimate is negative, which means that respondents in the software industry were much less likely to search for information about this item than were respondents in the pharmaceutical industry.

(Note that industry = 1 for the pharmaceutical industry, and industry = 2 for the software industry; therefore, an "increase" in the industry variable means going from the pharmaceutical industry to the software industry.)

This hypothesis received limited support. When examining the selection of any particular piece of information, experience and expertise have very little influence. This influence was limited to information search for the good concept, in which it was found that experience and expertise influenced the likelihood of searching for information about new competitive entries into a market. For the bad concept and the mixed concept, neither experience nor expertise were related to information search. However, a relationship between experience, expertise and information search cannot be ruled out because the small sample size of this study does not provide the power to find these relationships.

H9: Experience will be related to the amount of time spent in search.

Because novices and experts have different schema about product success and failure, they will consequently evaluate new product concepts differently. Experts should look at more pieces of information than will novices, which might mean that they will take longer than novices to come to evaluate a new product concept. However, experts' increased familiarity with the decision domain should make their search for information more goal-directed than novices, perhaps counteracting the time added by searching more items. In their study, Hershey, Walsh, Read, and Chulef (1990) found experts' problem solution to be more directed and efficient. They argued that the highly directed, goal-oriented search patterns of experts was evidence that experts had a script for problem solving which allowed them to be more efficient in their search. In any case, experience will be related to the amount of time spent in search.

Table 36 provides descriptive statistics for the amount of time spent in search. Also shown in the table are results of repeated measures t-tests on time spent in search. As shown in the table, respondents spent on average of 138.34 seconds searching the good concept, and 86.6 seconds searching the bad concept. This difference was significant ($t = 2.24$, $p = 0.03$) and was a medium effect ($d = 0.59$). This is consistent with findings presented previously on the number of items searched. Respondents spent more time searching the first concept than the second, and they also searched more information items for the first item than the second (see Table 23).

Examination of these means led me to wonder if the means in the two industries were statistically different. To test this, I conducted t-tests on the mean time spent in search by industry. Table 37 shows the results of these t-tests. As shown in the table, for two of the three new product concepts, there were significant differences in the mean time spent in search by respondents in the two industries. When searching for information about the bad concept, respondents in the pharmaceutical industry spent an average of 103.59 seconds searching for information, compared to an average of 64.41 seconds for the respondents in the software industry ($t = 2.50$, $p = 0.02$) . According to Cohen (1977), this difference is a medium effect (effect size $d = 0.66$). For the mixed concept, respondents in the pharmaceutical industry spent an average of 122.48 seconds in search compared to an average of 85.17 seconds for the software industry ($t = 1.71$, $p = 0.04$). This is a small effect ($d = 0.45$).

These results show that when information was unfavorable or mixed, respondents in the pharmaceutical industry spent much more time in search than did respondents in the software industry. This might imply that respondents in the software industry are much more risk averse than are respondents in the software industry. When information is bad, or simply not all good, respondents in the software industry stopped searching much sooner; respondents in the pharmaceutical industry were much more willing to stick with a concept and search for more information about it before making a judgment about it. Another explanation could be that respondents in the software industry are using a noncompensatory decision strategy in which they judge the concepts based on their values on one (or only a few) attributes. If so, if the concepts have negative values on the attributes of importance, then they do not search further. Respondents in the pharmaceutical industry might be using a more compensatory strategy, in which bad values on certain attributes can be compensated for by good values on other attributes. Using such a strategy would require the respondent to search more of the available information.

To test hypothesis H9, I regressed the total amount of time spent searching for information about each concept on experience and expertise. Because the amount of time spent in search was dependent on the respondent's industry for the bad and the mixed concepts, I tested the relationship between experience and length of time spent in search for these concepts separately for each industry. For the good concept, there were no industry effects, so I performed on regression for all respondents.

Since there were five regressions (one for the good concept, two each for the bad and mixed concepts) I used an adjusted level of significance of α = (0.10/5 =) 0.02. Only one regression was significant at this level, the regression for the mixed concept in the software industry ($F_{2,24} = 4.69$, $p = 0.02$). Results for this regression are shown in Table 38.

As shown in the table, the amount of time spent searching for information is related to both the decision maker's level of expertise and experience in the case where information is mixed or contradictory. The standardized parameter estimate for expertise is -0.48 ($t_{24} = -2.59$, $p = 0.02$), indicating that as expertise increases the amount of time spent in search decreases. However, the standardized parameter estimate for experience is 0.45 ($t_{24} = 2.42$, $p = 0.02$), indicating that as experience increases the amount of time spent in search <u>increases</u>. In this case, expertise and experience have the opposite effect on the time spent searching for information. This is somewhat counterintuitive, since the two measures are positively correlated.

So, hypothesis H9 receives partial support. Expertise and experience are related to the amount of time spent in search only in the software industry under conditions of conflicting or mixed information. The effects of the two variables on information search are conflicting, with expertise decreasing the time spent in search and experience increasing it.

H10: Experience will be negatively related to the use of cutoffs.

Because experts are hypothesized to have more elaborate schema than are novices, they should be able to make use of more information and more different types of information than novices when choosing among new product concepts. For this reason, they should be more capable of making use of a demanding compensatory decision rule. Less expert decision makers would be less likely to use a compensatory strategy because of their more limited ability to handle information.

Respondents were given the opportunity to state whether they would like to use cutoffs on several different variables to limit the number of new product concepts they would (hypothetically) have to evaluate. The four variables were: market size, market growth rate, the number of competitors, and the time from concept approval to product introduction (development time). To test this hypothesis, I regressed the decision whether to use cutoffs on the decision maker's level of experience or expertise. Before performing the regression, however, I crosstabulated the use of cutoffs by industry. These results are shown in Table 39. Of the 61 respondents who answered these questions: 51 (83.61%) said they would like to use a cutoff on market size; 41 (67.21%) said they would like to use a cutoff on market growth rate; 37 (60.66%) said they would like to use a cutoff on the number of competitors their product faced; and 36 (59.02%) said they would like to use a cutoff on the time from concept approval to product introduction (i.e., development time).

As shown in the table, the respondent's industry had a significant effect on his/her use of cutoffs on only one variable, the time from concept approval to introduction of the product (i.e., development time). Respondents in the software industry seem more likely to use a cutoff on development time than respondents in respondents in the pharmaceutical industry (X^2 with 1 df = 7.05, p = 0.008). Apparently, development time is a more critical issue in the software industry than in the pharmaceutical industry, perhaps because of the rapid introduction of new products.

Because industry had a significant effect on the use of cutoffs on development time, I regressed the use of cutoffs on development time on expertise and experience separately for the two industries. For the three other variables (market size, market growth rate, and the number of competitors) I aggregated the responses from both industries before running the regressions because the respondent's industry had no effect on the use of cutoffs. Each model used the form:

$$CUTOFF(variable) = \beta_0 + \beta_1 * EXPERTISE + \beta_2 * EXPERIENCE$$

where CUTOFF (variable) = the likelihood of using a cutoff on the variable in question
EXPERTISE = the composite measure of the respondent's expertise
EXPERIENCE = the composite measure of the respondent's experience

Table 40 shows the results of the logistic regressions on the respondent's use of cutoffs on market size, market growth rate, the number of competitors a new product would face, and development time.

As shown in the table, neither expertise nor experience were significant predictors of the decision to use cutoffs on market size, market growth rate, or the number of competitors a product faced. The -2 Log Likelihood estimate was not significant for either of the regressions for these variables. More expert or more experienced managers were no more likely to use cutoffs on these variables than were their less experienced or less expert counterparts.

The results were different for the use of a cutoff on development time. Though not true in the pharmaceutical industry, in the software industry the regression of the decision to use a cutoff on expertise and experience was significant (-2 Log Likelihood with 2 df = 5.21, $p = 0.07$). The standardized parameter estimate for expertise is -0.24 which was not significant (Wald $X^2 = 0.53$, $p = 0.47$). However, the standardized parameter estimate for experience is 0.64 (Wald $X^2 = 3.01$, $p = 0.08$). The likelihood of using a cutoff on development time increases as experience increases in the software industry. The odds ratio provides a way to determine the magnitude of the effect an increase in experience would have on the likelihood of using a cutoff. For this equation, the odds of using a cutoff on development time are estimated to almost triple (increase by 2.86 times) for each unit increase in experience.

So, hypothesis H10 is not supported. Experience was found to be influential in the decision to use a cutoff on development time to screen new product concepts, at least for respondents in the software industry. However, the relationship was opposite that hypothesized--experience was **positively** related to the use a cutoff on development time. This would seem to imply that experienced managers in that industry view development time to be a more crucial predictor of a product's chances for success or failure than do managers with less experience. The likelihood of using cutoffs on market size, market growth rate, and the number of competitors was not affected by the respondent's expertise or experience.

H11: Experience will be positively related to the value of the cutoffs used on different criteria.

To test this hypothesis, I regressed the cutoffs used on the four different available criteria (market size, market growth rate, number of competitors, and development time) on the respondents' experience and expertise. I did this only for the respondents who elected to use a cutoff on the different criteria. The regressions took the form:

$$CUTOFF=\beta_0+\beta_1*EXPERTISE+\beta_2*EXPERIENCE$$

where CUTOFF = the cutoff used on a particular variable
EXPERTISE = the composite measure of the respondent's expertise
EXPERIENCE = the composite measure of the respondent's experience

Before I ran the regressions, I conducted t-tests on the four different cutoffs to determine if the actual cutoff used depended on the respondent's industry. Table 41 shows the results of these tests. As shown in the table, the value of the cutoffs did differ by industry for three of the four variables on which cutoffs could be placed. These were market size, market growth rate, and development time. However, no significant industry differences were found for the cutoff on the number of competitive products a concept might face.

As one might expect, given the markets involved, respondents in the pharmaceutical industry had a much higher cutoff on market size than did respondents in the software industry. The mean cutoff for respondents in the pharmaceutical industry was $142 million, while the mean in the software industry was $16.73 million, almost an order of magnitude smaller. The difference in the means is significant ($t = 3.33$, $p = 0.002$) and, with an effect size of 0.95, is a large difference (Cohen 1977).

Respondents differed on the value a concept would need to have on market growth rate to be considered, but this time respondents in the software industry were more stringent. The mean cutoff on market growth rate in the software industry was 18.88%, whereas it was 10.52% in the pharmaceutical industry, a difference that was both significant ($t = -3.36$, $p = 0.002$) and large ($d = 1.08$).

As might be expected, the cutoff on development time also differed by industry. The mean cutoff in the pharmaceutical industry was 3.9 years, while it was 1.10 years in the software industry. Again, this difference was significant ($t = 3.44$, $p = 0.004$) and large ($d = 1.18$).

Comparing the two industries, it would seem that respondents in the pharmaceutical industry are more interested in new product concepts for large markets but less stringent about at what rate that market must be growing than their counterparts in the software industry. Respondents in the software industry seem to be interested in fast growing markets which may be relatively small, and they feel it necessary to get new products to the market quickly. Their cutoff on development time, 1.1 years, was less than one third the time respondents in the pharmaceutical industry used as a cutoff for acceptable concepts (3.9 years). The long time period to obtain FDA approval for pharmaceutical might be a factor in this difference.

Interestingly, respondents in the two industries did not differ significantly on the maximum number of competitors a new product could face to avoid being screened out; differences in the means (7.05 competitors for the pharmaceutical industry vs. 6.00 for the software industry) were not significant ($t = 0.77$, $p = 0.45$).

Because of the significant differences in means discussed above, I regressed the cutoff on experience and expertise separately by industry for all variables except the number of competitors, on which there was no significant difference. For the cutoff on the number of competitors, I aggregated all responses. The results of these regressions are shown in Table 42.

<u>Cutoff on Market Size</u>: As shown in the table, the regression of the market size cutoff on expertise and experience is significant in both industries (in the pharmaceutical industry: $F_{2,27} = 4.59$, $p = 0.02$; in the software industry: $F_{2,18} = 6.2$, $p = 0.009$). The coefficient of determination, R^2, in the pharmaceutical industry was 0.25, while it was 0.41 in the software industry, which indicates that the model did a reasonable job of explaining the variance in the value of the cutoff on market size in both industries.

In the pharmaceutical industry, both expertise and experience have significant impact on the value of the cutoff. Interestingly, the two variables have opposite effects on the cutoff. The standardized parameter estimate for expertise is 0.42 ($t = 2.38$, $p = 0.02$) while it is -0.45 ($t = -2.56$, $p = 0.02$) for experience. So as expertise increases, the cutoff on market size increases (becomes *more* stringent); however, as experience increases, the cutoff size decreases (becomes *less* stringent).

In the software industry, expertise *was not* a significant predictor of the cutoff on market size ($\beta = -0.06$, $t = -0.30$, $p = 0.77$), but experience was ($\beta = 0.66$, $t = 3.41$, $p = 0.003$). So, in the software industry, as experience increases the cutoff on market size increases (becomes *more* stringent), the opposite to the effect of experience in the pharmaceutical industry.

Cutoff on Market Growth Rate: As shown in the table, the regression of the cutoff on market growth rate is not significant in either industry (in the pharmaceutical industry, $F_{2,22} = 0.52$, $p = 0.60$; in the software industry, $F_{2,13} = 1.51$, $p = 0.26$). This implies that neither expertise nor experience has any effect on the cutoff on market growth rate. However, since few managers in either industry elected to use a cutoff on this variable, the sample sizes are small which may lead to power too low to detect a relationship. For example, according to Cohen (1988), the power of the regression in the software industry has a power of approximately 0.15 at the $\alpha = 0.01$ level (the lowest α for which tables are provided). (See Cohen (1988), Table 9.3.1 for $R^2 = 0.19$, $u = 2$, $v = 13$, and $\lambda \approx 4$).

Cutoff on Development Time: The regression of the cutoff on development time was significant, but only in the pharmaceutical industry ($F_{2,12} = 3.03$, $p = 0.09$). In the software industry, the regression was not significant ($F_{2,18} = 1.16$, $p = 0.34$). In the software industry, neither experience nor expertise has any affect on the cutoff used on development time.

Examining the standardized parameter estimates in the pharmaceutical industry shows that only expertise is a significant predictor of the cutoff on development time ($\beta = -0.62$, $t = -2.39$, $p = 0.03$). The parameter estimate for experience was *not* significant ($\beta = 0.12$, $t = 0.47$, $p = 0.65$). So, as expertise increases, the cutoff on development time decreases, which implies that more expert managers are more willing to consider product concepts with longer development times than are less expert managers.

Cutoff on the Number of Competitors: The regression of the cutoff on the number of competitors a new product concept would face was not significant ($F_{2,33} = 0.50$, $p = 0.61$). Neither expertise nor experience affected the value chosen for this cutoff.

Hypothesis H11 was partially supported. The respondents' levels of expertise and experience did influence their cutoffs, but not for every variable. The influence of the two also differed by industry. Specifically, expertise and experience influenced the cutoffs on market size in the pharmaceutical industry, but only experience was influential in the software industry. In the pharmaceutical industry, expertise was negatively related to the cutoff on development time, but experience had no influence. In the software industry, the cutoff on development time was not related to either expertise or experience.

Expertise and experience had differing effects on respondents' cutoffs. In the pharmaceutical industry, expertise had the effect of increasing respondents' cutoffs on market size, implying that when screening new product concepts on market size, managers with more expertise would be more stringent than would those with less expertise. However, experience was negatively related to the cutoff on market size, so decision makers with more experience would be less stringent when screening by market size than those with less experience. This seems to be an interesting contradiction, since it seems reasonable to assume that expertise is gained with experience.

In the software industry, experience had the opposite effect. Experience had the effect of increasing respondents' cutoffs on market size, implying that when screening new product concepts on market size, managers with more experience would be more stringent than would those with less experience. Expertise had no effect in this industry.

The results of the regression on development time are quite interesting. Here, expertise did have an effect on the cutoff but only in the pharmaceutical industry. In that industry, it was negatively related to the value of the cutoff, implying that as respondents became more expert, the cutoff became less stringent. Therefore, more expert decision makers seem willing to consider concepts which might take longer to develop than would their less expert counterparts. In the software industry, expertise had no effect on the cutoff. In neither industry did experience have any effect on the cutoff.

H12: Experience will be related to the evaluations of new product concepts.

Due to their use of different information and the differences in the way they put this information together, less experienced and more experienced managers may make different evaluations about new product concepts.

In actuality, respondents had to make two different evaluations of each product concept. First, they had to decide if the concept should be sent on to development or if it should be rejected and receive no further attention. Then, they were asked to rate the likelihood of its eventual success or failure in the marketplace. So, H12 is really hypothesizing two relationships, which I will call H12a and H12b. These are:

H12a: Experience will influence whether a respondent sends a new product concept on to the next stage of development.

H12b: Experience will influence respondents' evaluations of the new product concept's chances of success or failure.

Table 43 shows crosstabulations of the respondents' decisions to send the three new product concepts on to the next stage of development by industry. Fifty-five of the 60 respondents who evaluated the good concept decided to send it on to the next stage (91.6%). The bad concept did not fare so well; only 6 of 60 (10%) of the respondents sent it on. Finally, 20 of 61 respondents (32.8%) sent the mixed concept on to development. Examining the resulting X^2 for each crosstabulation shows the respondent's industry did not effect this decision.

Note that there is a lack of variation in the decision for the good and bad concepts. With a very high proportion of respondents making the same decision, the ability to test these hypotheses will likely be limited.

After deciding whether each concept should be further developed, I then asked respondents to evaluate the likelihood of success or failure. This rating was on an 11-point scale, where -5 = extremely likely to fail and 5 = extremely likely to succeed. The mean ratings of the three concepts are shown in Table 44. The table also shows results of t-tests on these mean ratings by industry and the results of repeated measures paired t-test to see if ratings of the three concepts were statistically different..

In general, respondents ratings show that they perceived the concepts as I had intended. The good concept had a mean rating of 2.43. Respondents perceived that it was likely to succeed. In contrast, the ratings of the bad and the mixed were perceived as being likely to fail. The mean rating of the bad concept was -2.81. The mean rating for the mixed concept was -1.29, less negative than the bad concept, but still likely to fail. Paired t-tests showed that the ratings of the three different concepts were statistically different. The mean difference between ratings of the good and bad concepts was 5.24, which was a large effect ($t = 18.58$, $p = 0.0001$, $d = 4.9$). The difference between the bad and the mixed concepts was smaller (mean difference = -1.49), but still significant and large ($t = -3.94$, $p = 0.0002$, $d = 1.03$). Finally, the difference between the mixed and the good concept was -3.75, which was also significant and large ($t = -9.72$, $p = 0.0001$, $d = 2.55$). Thus appears that the negative information for the mixed concept was heavily weighted, as previous research would suggest.

Examining the t-tests of ratings by industry shows that both groups of respondents rated the good concept favorably; the mean rating by the pharmaceutical respondents was 2.66, while it was 2.13 in the software industry. This difference was not statistically significant ($t = 1.30$, $p = 0.20$). Similarly, mean ratings of the mixed concept were -1.32 for the pharmaceutical industry and -1.24 for the software industry. Again, this difference was not statistically significant ($t = -0.11$, $p = 0.91$).

There was, however, a significant difference between the mean ratings of the two groups on the bad concept. Though both groups rated this concept as being likely to fail (pharmaceutical mean = -2.22, software mean = -3.59), respondents in the software industry rated it much more negatively than did respondents in the pharmaceutical industry. This difference was statistically significant (t = 3.42, p = 0.001) and meaningful (d = 0.90, which is a large effect). This seems to imply that when the information about a new product concept is favorable or when it is mixed, respondents in the two industries make similar evaluations of its chances for success or failure. However, when the information about the concept is unfavorable, respondents in the software industry are much more harsh in their evaluations of its chances for success than are respondents in the pharmaceutical industry. This might indicate a more competitive environment in which a concept with unfavorable values on some attributes stands a much smaller chance of success.

H12a: To test H12a, I used logistic regression to test whether the respondents' levels of expertise and experience were predictors of the decision to send the concept on for further development. Since no industry differences were apparent in this decision, I aggregated all responses. The models took the form:

$$GO_i = \beta_0 + \beta_1 * EXPERTISE + \beta_2 * EXPERIENCE$$

where GO_i = the outcome of the Go/NoGo decision for the *i*th concept (0 = No Go, 1 = GO)
EXPERTISE = the respondent's level of expertise
EXPERIENCE = the respondent's level of experience

Table 45 shows the results of these regressions for each new product concept. This table shows the - 2 Log Likelihood estimate, the corresponding p-value for the regression, the standardized parameter estimates for the independent variables, and the p-values for tests of significance for the parameter estimates, and the odds ratios for each parameter (if significant in the equation). As shown in the table, Hypothesis H12a is partially supported. The regression of the Go/NoGo decision on experience and expertise was significant for the good concept and the bad concept, but not for the mixed concept. For the good concept, the -2 Log Likelihood estimate is 4.88 (p = 0.09) and for the bad concept it is 4.82 (p =

0.09). For the mixed concept, the -2 Log Likelihood estimate is 1.36, which is not significant ($p = 0.51$). It is interesting to note that neither expertise nor experience provide any benefits under conditions of mixed information. One might have expected that this is when experts' more elaborate schema might have helped them make sense out of conflicting information.

Examining the standardized parameter estimates for the good concept shows that expertise is a significant predictor of the Go/NoGo decision ($\beta_1 = -0.45$, $p = 0.08$) but experience is not ($\beta_2 = -0.41$, $p = 0.53$). The parameter estimate for expertise is negative, implying that as expertise increases the likelihood of sending the concept on for further development decreases. The odds ratio of 0.429 indicates that for each unit increase in expertise, the odds of sending the concept on decrease to 42.9% of their previous value.

Results for the bad concept are similar to those for the good concept. Again, expertise is a significant predictor of the Go/NoGo decision ($\beta_1 = -0.65$, $p = 0.08$) but experience is not ($\beta_2 = 0.51$, $p = 0.23$). The parameter estimate for expertise is negative, implying that as expertise increases the likelihood of sending the concept on for further development decreases. The odds ratio of 0.292 indicates that for each unit increase in expertise, the odds of sending the concept on decrease to 29.2% of their previous value.

It is interesting that the parameter estimates for expertise are significant and negative for both the good and bad concepts. Since the two concepts represented two different decision contexts, this implies that more expert decision makers are more cautious about sending a concept on for further development regardless of the concept's "goodness" or "badness." That is, when information about a concept is generally good *or* generally bad, expert decision makers are more likely to kill it than their less expert counterparts. Decision makers with more expertise seem to be more risk averse. Interestingly under conditions of ambiguity (the mixed concept), expertise plays no role in the respondent's Go/NoGo decision. This is counterintuitive because it would seem that expertise should become most useful on close calls, those decisions which in which it is not clear what the outcome of the decision should be.

H12b: To test hypothesis H12b, that experience will influence respondents' evaluations of the new product concept's chances of success or failure, I regressed their evaluations of the product concepts on expertise and experience. The equations took the form:

$$RATING = \beta_0 + \beta_1 * EXPERTISE + \beta_2 * EXPERIENCE$$

where RATING = the respondent's rating of the concept's chances for success or failure on an 11-point scale (-5 = extremely likely to fail, 5 = extremely likely to succeed)
EXPERTISE = the respondent's level of expertise
EXPERIENCE = the respondent's level of experience

Because there were no industry differences in the ratings for the first and third concepts, I aggregated the results for those concepts. However, since respondents in the two industries did rate the second concept differently (see discussion above), I ran the regressions separately for each industry. Table 46 shows the results of these regressions. For each regression, the table gives the F-value, the p-value, the standardized parameter estimates for expertise and experience, and the significance tests associated with these parameter estimates.

As shown in the table, Hypothesis H12b is partially supported. The regression of the rating of the good concept on experience and expertise is significant ($F_{2,57}$ = 2.66, p = 0.08). Examination of the parameter estimates shows that expertise is a significant predictor of the rating of this concept (β_1 = 0.30, t = 2.21, p = 0.03) but experience is not (β_2 = -0.02, t = -0.14, p = 0.89). Since the parameter estimate for expertise is positive, the rating of the concept becomes more favorable as expertise increases.

Neither of the regressions for the bad or mixed concepts were significant. Neither expertise nor experience were significant predictors of the evaluations of concepts for which information was uniformly unfavorable or mixed.

Comparing results of the hypothesis tests for H12a and H12b leads to an interesting contradiction in respondents' evaluations of the good concept. Expertise was a significant predictor of the likelihood of this concept being sent on the next stage of development and of its evaluation. However, as discussed previously, as expertise increased, respondents were less likely to send it on for further development. Despite this, as expertise increased, the evaluation of the concept increased. So even though more expert decision makers felt it was more likely to succeed than did their less expert counterparts, they were less likely to further develop this concept.

Summary of hypotheses tests: The hypotheses tested in this study received mixed support. For the most part, some evidence was found to support the belief that expertise and experience are influential in the concept screening process. Two notable exceptions were the relationship between experience, expertise and attributions and experience, expertise and the use of cutoffs. Figure 7 shows the conceptual model which guided this study modified to indicate which relationships were supported and which were not.

There was no evidence that experience or expertise had any affect on the number of attributions respondents made for success or failure. Neither did they have any affect on what those specific attributions were. This might imply that more and less experienced managers possess similar schema for product success and failure. However, it cannot be ruled out that the simple measure used here to try to get at these schema did not allow for a strong test of these relationships.

For three of the four variables on which they could elect to use cutoffs, there were no differences in the use of cutoffs due to experience or expertise. However, in the software industry, more experienced managers were more likely to use cutoffs on development time than were their less experienced counterparts. This finding was contrary to the hypothesis originally made. At least in the software industry, there is evidence that the processing strategy used by more experienced managers is not a compensatory strategy, despite their supposedly greater ability to make use of more of the available information than less experienced managers.

Discussion and Conclusions

This study was designed to make contributions to our understanding of managerial decision-making in the context of screening new product concepts. In this chapter, I will discuss the managerial implications of my findings as well as the contributions I believe this work has made to the academic literature. I will also discuss limitations of this work and directions for future research.

Managerial Implications

Attributions: This work has highlighted some interesting facets of managers' thinking about new products and their decision making behavior when evaluating them. One interesting finding is that managers' top of the mind beliefs about new product success and failure are extremely idiosyncratic. There seems to be little consensus, even among managers in the same industry, as to what factors cause a new product to succeed and what causes it to fail. In this study, managers came up with 75 different factors to which they attributed new product success or failure. Very few of these factors, however, were listed by as many as 20% of the managers.

This idiosyncracy in belief systems may be a source of difficulty or conflict in the screening of new product concepts. Since new product concept screening in many companies is done by groups of individuals working together, decision makers could hold many varied and conflicting beliefs about product success and failure. To minimize conflict, managers must be sure to adequately discuss these differences and come to some consensus so that the evaluation process may flow more smoothly. If it does not lead to conflict, this idiosyncracy may be useful in the screening process. The many different viewpoints and beliefs might lead to a better decision in the long run, if those involved use them to challenge potentially harmful assumptions about the product, the market, etc.

Why and how managers develop these myriad beliefs about new product success and failure was not answered by this study. However, it did show that in general, managers in this study have received very little formal training in new product concept screening, which may account for the great variety in beliefs. If a company wanted to directly influence its managers' beliefs, it might engage in more formal training methods which might minimize some of the idiosyncracy of beliefs.

Findings of this study show that, in general, managers feel that product successes are due largely to the product's characteristics and that failures are due to factors largely under the company's control. This paints a more positive picture of managers than previous research which found that managers made self-serving explanations of failures and successes (Bettman and Weitz 1983). Most managers in this study did not seem to feel that actions outside the company's control (such as government regulation or competitive actions) had much influence on a new product's chances for success or failure. If these beliefs are true, then managers should feel that a product's chances for success and failure are largely under the company's control and that ensuring success and avoiding failure are a matter of doing the right things right and not doing the wrong things. Managers in this study felt that to ensure success and avoid failure, companies need to ensure that:

- the product offers a meaningful advantage to users;

- the product is very well differentiated from the competition;
- the price is right and that the product offers consumers real value;
- marketing support and market research for the product are adequate.

More than two thirds of respondents stated that the most common reason for a product's success is that it offered consumers a meaningful advantage over existing products. Though this may sound obvious, the high number of "me-too" products in today's marketplace may be an indication that many companies have forgotten this. Instead of merely copying a competitor's product or offering minor modifications which offer no real advantage to the consumer, managers in this study seem to be saying that a company's time may be better spent trying to deliver a product which is <u>really</u> better from the consumer's point of view.

The most commonly stated reason for failure was inadequate marketing support for the product, which was cited by 43.5% of respondents. This paints a disturbing picture of the process of developing and launching a new product. After spending a great deal of time, money, and human resources to develop a new product, managers seem to be saying that companies then waste this effort by not adequately supporting the product. Since the level of marketing support given a product is largely under the company's control, the incidence of this factor's causing a product to fail could be minimized by upper management ensuring that adequate resources exist within the company to support the product and that these resources are delivered when needed. Since very few managers cited too many products being in development at the same time as being a cause of failure, it does not seem that this situation exists because available marketing resources are spread across too many projects; rather, it seems to be a problem of understanding what level of support is needed or the willingness or ability to provide those resources. Managers must put forth every effort to ensure that they understand the marketing needs of each product and that they can provide for those needs.

Of course, attributing failure to inadequate marketing support for the product could be a self-serving attribution if the respondent did not have control on the allocation of resources within the company. In effect, respondents making this attribution are blaming others for the product's failure. If so, this is consistent with Bettman and Weitz's (1983) finding.

Finally, it is interesting to note that managers' attributions for product success and failure did not differ greatly by industry. This could be due to the large amount of variability in attributions within each industry. It could also be true that though the two industries involved differed in many ways, such as the level and nature of competition, the amount of government regulation, and the size of the markets in which they competed, managers in the two industries had similar beliefs about what causes products to succeed or fail.

<u>Diagnosticity</u>: In this context, diagnosticity is the ability of a piece of information to predict whether a product will succeed or fail. It is important for those in the company responsible for setting up marketing information systems to know what information is considered diagnostic by managers so that they may be sure that this information is collected. Also, those involved in market research need

to know managers' beliefs about diagnosticity in order to provide decision makers with the information they need to evaluate new product concepts.

In this study, managers found one of the most diagnostic types of information to be information about the product itself. This included information about whether a new product concept offered a meaningful advantage to users, its level of differentiation from competitors, its likely price position, and its quality. This implies that managers have accepted the normative prescription that the key to a product's success is obtaining a competitive advantage over the competition (Kerin, Mahajan, and Varadarajan 1990; Kotler and Armstrong 1994). This is also consistent with the diffusion of innovation literature, which states that the relative advantage of a new product over existing products influences its adoption (Rogers 1983). To determine if the product does have this advantage, the company needs to do enough market research to determine how the product compares to its competition and whether consumers see its differences as real advantages. This information is critical in predicting whether a product will succeed or fail. Managers also need to ensure that the consumers must view the product's price and quality favorably in comparison to the competition.

Managers' diagnosticity ratings showed that they believe that the level of upper management support for the product is also very diagnostic of future success or failure. This acknowledges the political reality of new product development in many companies, a reality in which a product without adequate support from top management may have bleak prospects for future success, despite its positive qualities on other attributes. The level of upper management support seems to be more diagnostic than many other factors often cited by the normative literature, such as the market characteristics and the product's match to existing products or product lines. Perhaps this points out the need for the normative literature on new product development to address organizational, political, and social issues within the company which may affect new product concept screening.

Expertise and experience: This study shows that managerial expertise and experience impact on the decision making process regarding new product concepts. In this study, experience was measured as a combination of industry tenure, tenure in new product development, and the number of new product decisions in which the respondent was involved. The study provides little insight into the antecedents of expertise, though there is an indication that it may be related to the type of training received. The two constructs are related, but not strongly. They are different and have different effects on managerial decision making.

There is some evidence that expertise is related to the perceptions of diagnosticity, or the predictive usefulness, of information. Most notably, as expertise increases, there is an increase in the perceived diagnosticity of product quality and a decrease in the diagnosticity of the number of other products in development. As managers gain more expertise, they place more value on information about the product's quality and less on the number of other products in development which may be competing for resources. There is also evidence that experience may be related to managers' perceptions of the predictive usefulness of information. As experience increases, the diagnosticity of management's level of experience with the necessary technology, whether existing supply channels can be used, and the likelihood of adverse government regulation increase.

Expertise and experience also seems to influence managers' search for information. Under conditions of favorable information and mixed (conflicting) information, increased expertise or experience led to less information search. This may point out that expertise and experience increase managers' efficiency in searching for information, which may provide benefits such as savings in the time and other resources necessary to collect information. However, making decisions with less information may not be wholly positive. This may be an indication that expertise leads to overconfidence in decision-making, which may compromise the quality of those decisions (Mahajan 1992). It may be important for companies with managers who consider themselves expert or experienced in new product concept screening to provide an incentive for those managers to thoroughly examine important and relevant information about a new product concept before making a decision about it.

Both expertise and experience were related to the amount of time spent searching for information about a new product concept with conflicting information before rendering a judgment about it. In this case, the two constructs had opposite effects. As expertise increased, the amount of time spent searching decreased. However, as experience increased, the amount of time spent searching increased. This may point out a negative consequence of expertise. While it may be possible that experts spent less time in search because their increased understanding of the decision domain allowed them to come to a decision more quickly, another explanation is that this may again point to expert's overconfidence in their own decisions (Mahajan 1992). This overconfidence allows decision makers to make judgments more quickly with less information.

Experts' tendencies to make decisions with less information and in less time may seem desirable if one believes that their decisions are "right" or are better than the decisions of those with less expertise. However, there is evidence to suggest that this might depend on how decision makers are determined to be experts. Larréché and Moinpour (1983) report that experts identified by a simple external measure of expertise provided better estimates in a forecasting task than did those who were not identified to be experts by this measure. However, experts identified by a self-rated confidence measure did not provide better estimates than those who did not rate themselves to be experts.

Experienced or expert decision makers were no more or less likely than their less experienced, less expert counterparts to use cutoffs on market size, market growth rate, or the number of competitors a product might face. However, experience was related to the use of cutoffs when screening new product concepts, but only in the software industry. In that industry, more experienced managers were more likely to use a cutoff on development time than were less experienced managers.

Both expertise and experience were related to the value of the cutoffs chosen for certain criteria. The relationships between the variables are complicated, though, as the effects varied by criteria and by industry. There was no relationship between expertise and experience and the value of cutoffs on market growth rate and the number of competitors, so for these two criteria less and more expert or experienced decision makers used similar cutoffs.

However, expertise was related to more stringent cutoffs on market size in the pharmaceutical industry, while experience led to lower cutoffs. In this industry, then, there seems to be some conflict about the potential market size a new product concept should have. More expert decision makers seem to feel that a product must have to have a larger market to be considered than do less expert decision makers. However, those with more experience have a less stringent cutoff than those with less experience, so they are willing to consider products with smaller market potential.

In the software industry, as experience increases so does the cutoff on market size. So more experienced managers have more stringent cutoffs on market size than do their less experienced counterparts.

In the pharmaceutical industry, more expert managers have lower cutoffs on development time than do less expert managers. So, more expert managers are willing to consider products which may take longer to develop than are less expert managers.

Finally, expertise (but not experience) seems to have an effect when making decisions about new product concepts. When information about a concept is uniformly good or is uniformly bad, as expertise increases the likelihood of sending the concept on for further development decreases. So more expertise is associated with a greater likelihood of killing the concept when all available information about the concept is good or bad. Despite this, expertise was related to rating the good concept as having a higher chance for success. So, even though they thought that the product had a greater chance for success than did their less expert counterparts, more expert managers were still more likely to kill the concept. This seems to be contradictory in that one might expect a person who rates a concept as having a higher likelihood of success than another person to be more likely to want to further develop that product. It could be, however, that more expert decision makers are more reluctant to commit the company's resources to any product unless that product is exceptional, not just good. It seems that more expert decision makers are more risk averse than are less expert decision makers.

As this study shows, expertise and, to a lesser extent experience, are both influential in managers' information search. Expertise is also influential in their decision making about new product concepts. Because of this, it is important to understand the antecedents of expertise and experience. This study sheds some light on what constructs make up experience, but provides little information about what makes someone perceive him/herself to be an expert. However it comes about, though, expertise is important from a managerial standpoint because more expert decision makers do act differently in new product concept screening than their less expert counterparts. This study did not determine if experts' decisions were better, but it did determine that their decisions are different. Further research might show whether their decisions are better and if so, how to train less expert decision makers to emulate their behavior.

It must be acknowledged that expertise might not lead to better decisions. Further research might determine if expertise is an asset or a liability when it comes to new product concept screening. If it is a liability, companies might wish to implement techniques or incentives to overcome the liabilities of expertise.

Theoretical Contributions

This study has made several contributions to several different bodies of literature. These include the literature on expertise and experience and their effects on decision making, the accessibility-diagnosticity theory, and the literature on new product concept screening.

Contributions to the expertise/experience literature: First, this study has extended the theory of expertise to the domain of managerial decision making. Measures of expertise and experience developed for this study seemed to be domain-specific measures of expertise and experience in new product concept screening. They also were found to have good reliability, considering the exploratory nature of this study. The expertise construct was found to be conceptually distinct from the experience construct, though they were significantly correlated (the correlation between the two measures was 0.36).

The fact that the two constructs are related but distinct makes it imperative that further studies into managerial expertise and its effect on decision making do not use experience as a surrogate for expertise. Studies of expertise using managers often use experience as a surrogate for expertise (Perkins and Rao 1990; Isenberg 1986). Because it is much easier to measure, it is understandable that experience might be used in this way. However, the present study points out that the two constructs are different and have different effects on the decision making process; any study using one when it ostensibly means to use the other will only cloud issues and limit our understanding of either construct's affect on decision making.

It is also important to note here that how one measures expertise could influence one's findings. Larréché and Moinpour (1983) have shown that expertise measured externally provides different findings than a self-rated measure of expertise. The findings presented here could be dependent upon the self-rating measure of expertise used; the relationships between expertise, diagnosticity, and information search may well be different if a different measure of expertise were used.

Though there was some doubt that expertise would have any effect in an ill-structured decision, the findings of this study show that expertise does affect decision making behavior even in the context of new product concept evaluation, which can be considered an ill-structured or nonprogrammed decision (Simon 1960; 1973). This is important because many, if not most, of the decisions that managers must make can be considered non-programmed or ill-structured in that they have few guidelines for problem solution and there is often no one "right" solution. This study provided evidence that expertise and experience did influence managers' ratings of the diagnosticity of information, the search for information when evaluating new product concepts, and the actual evaluations of the concepts themselves. However, it must be acknowledged that the format of the study did impose a great deal of structure on what is a generally unstructured decision. Thus, the effect of expertise on the actual process of evaluating new product concepts might be different from the effects found here.

This study also showed that decision contexts might influence the relationship between expertise and information search and the evaluations made. Under conditions of uniformly good information or uniformly bad information, expertise was negatively related to the likelihood of terminating a new product concept. Surprisingly, under conditions of conflicting or mixed information, expertise was not related to the likelihood of terminating the concept. However, it was related to less information search. This shows that when expertise might be the most useful, as when the information is mixed and it is not clear what should be done, the only benefit provided by expertise might be in the more efficient and less time-consuming search for information.

<u>Contributions to the literature on the accessibility-diagnosticity theory</u>: Feldman and Lynch (1988) originally proposed the accessibility-diagnosticity theory to explain the search for information in memory. This study shows that the construct of diagnosticity has applications in external information search. The measures of diagnosticity used in the pretest provided reasonable convergent validity of the diagnosticity construct. The measure used the final study succeeded in distinguishing the predictive usefulness of different types of information a decision maker might obtain about a new product concept.

Diagnosticity was found to be related to the attributions made about new product success and failure and to managers' search for information when evaluating new product concepts. Factors to which new product success and failure were attributed received higher ratings of diagnosticity than did factors to which managers did not attribute success or failure. Diagnosticity was also found to be related to the likelihood of a piece of information being searched and the order in which it was searched. The higher the diagnosticity, the more likely an item was to be searched and the sooner it was to be searched.

Contributions to the literature on new product concept screening: This study provided information about managers' perceptions of the predictive usefulness of different types of information they might use when evaluating new product concepts. Many of the criteria suggested for new product concept evaluation by the normative literature were perceived by managers as being predictive of a product's chances for success or failure. In contrast to Ronkainen's (1985) study, most managers stated that they did use financial criteria to judge new product concepts.

Contrary to Ronkainen's (1985) findings, market criteria were not considered to be the most diagnostic at the concept evaluation stage. Managers in this study rated product factors, such as whether the product offered a meaningful advantage to users, its level of differentiation from competitors and its comparative quality, as being more important in new product concept evaluation than were such market criteria as projected market share and market growth rate.

Limitations of the study

The most obvious limitation of this study was the relatively small sample. Though a sample of 62 managers is comparable or larger than other studies on managerial decision making (Isenberg 1986; Perkins and Rao 1990), this number offered limited power to test many of the relationships under investigation. For example, the power to find significant correlations at the r = 0.20 level (the magnitude of the correlations between experience and some of the diagnosticity ratings) at the $\alpha = 0.10$ level with 60 respondents is only 0.46 (Cohen 1988). Though I do not have the means to determine the power of a logistic regression, it is not difficult to imagine that the power for these tests might be low also, especially in cases where I split the sample in two by industry. Despite this, many of the hypotheses did receive partial support, so even with the small sample size, there is evidence that something of interest did occur. Collecting more data would increase the power to test these relationships.

Another possible threat to the strength of the hypothesis tests was the lack of variability in respondents' levels of expertise. The standard deviations of both the perceived knowledge measure and the perceived expertise measure were 1.80 and 1.95 on a 9-point scale, respectively. This lack of variation could seriously weaken any hypothesis test involving the expertise construct. To increase the strength of these tests, it might be necessary to increase the variability in expertise. This may be accomplished by more actively recruiting decision makers in organizations with less expertise in new product concept screening.

A potential source of bias in the study is due to the low response rate. Possible nonresponse bias might make the results of this study not generalizable to the populations sampled. To check this, I compared the sizes of companies that were mailed questionnaires but did not send them back against companies that did. There were no differences in company size. Though company size might not be related to managers' behavior in new product concept screening, this variable was one of the few available about the companies in the study, most of which are private, making it difficult to gather other types of information about them.

I also kept track of the amount of time it took respondents to send their questionnaires back as there is some evidence that late respondents are more like nonrespondents than are early respondents (Rosenthal and Rosnow 1984). There were no differences on any measure of interest between early respondents and late respondents.

In terms of the specific measures used in this study, further work in this area might be more successful if two of the measures are changed. First, the simple measure I used to gather respondents' attributions about new product success and failure might not have provided a true measure of the complexity of managers' beliefs. Future work in this area might want to use a measure that encourages managers to elaborate more fully on their belief systems. For example, interviews using probing questions might elicit more elaborate schema. Axelrod's (1976) method of developing cognitive maps might also provide a more in-depth understanding of managers' belief systems.

Another improvement might come about through changing the endpoints of the diagnosticity scale to encourage respondents to make fuller use of it. With the current scale, respondents rated most items as having diagnosticity between six and eight. It seems that respondents were reluctant to use the lower two thirds of the scale because they did not want to label many of the items as nondiagnostic. Perhaps if the lower endpoint, which is currently labeled "Not at all useful in predicting success or failure," were changed to "Somewhat useful in predicting success or failure" respondents might be encouraged to use the lower part of the scale, because then the lower ratings would not indicate that a piece of information was virtually useless, only that it was less diagnostic than other pieces.

Despite these problems, this study made meaningful contributions as described above. It also highlights some interesting areas for future research. First, though this study developed a reasonable measure of perceived expertise in new product concept screening, this construct still needs further work as the third measure I used (the frequency of seeking advice) did not seem to be measuring perceived expertise. Secondly, does the way in which expertise is measured influence its effects on decision making behavior? For example, could an external measure of expertise be developed and used to validate the self-measure? Would the effects of expertise using this external measure be different than the effects on decision making found here? This study provided evidence which showed that expertise is important because it affects many aspects of decision making. But how is this expertise obtained? What factors influence a decision maker's perceptions of his/her expertise? Further research could investigate this question to determine how expertise is obtained and if different methods are more successful than others at conferring expertise on an individual.

There were also differences in decision making due to experience. This raises several questions, such as: What specific type of experience (industry experience, specific experience in new product development, etc.) influences decision making? Through what mechanism does experience effect expertise? Why do experience and expertise have different effects on decision making?

A still more basic issue is whether expertise leads to better decisions. This study shows that expertise leads to differences in information search and concept evaluation, but are the decisions of more expert decision makers better than those of less expert decision makers? There is evidence that expertise may lead to overconfidence, which may lead to poorer decisions (Mahajan 1992). Future research needs to try to answer this question, especially since expert systems are being developed to screen new product concepts (Mahmood and Sullivan 1992; Ram and Ram 1989). If experts' decisions are no better than or are even worse than those of novices, we must know this before we can advocate the use of expert systems to aid in new product concept screening.

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Table 1. Suggested Criteria for New Product Concept Evaluation

1. Match to Organizational Objectives and Capabilities

Match to organizational profit, market share goals
Existence of necessary financial resources
Match to marketing capabilities
Match to existing technology/R&D experience
Management skills/experience with product-market

2. Match to Existing Products or Product Lines

Match to physical distribution system
Ability to use existing salesforce
Ability to service product
Compatibility with other products
Effect on sales of present products
Overlap with current materials supply channels

3. Market Characteristics

Sales Potential

- Market size
- Growth rate of sales
- Market breadth or scope

Scale

- Potential for significant market share
- Significance of experience curve

Stability

- Resistance to seasonal/cyclical fluctuations

Penetration

- Cost of entry
- Time to become established
- Vulnerability of competition
- Potential for product advantage for users

Table 1, Cont'd.

4. Investment Analysis

Net present value
Maximum capital input necessary (including marketing effort)
Payback period
Internal rate of return (IRR)
Cash flow analysis
Return on investment (ROI)

5. Competitive Factors

Number of existing or potential competitors
Size of competitors
Competitors' resources
Likelihood of competitive entry into market
Probability of competitive retaliation

6. Profitability

Margin size
Profit potential

7. Risk

Probability of technical completion
Rate of technological change in product-market
Possibility of adverse regulation
Stability of demand
Complexity of market research needed
Compatibility with existing attitudes and method of use
Amount of learning necessary for product use
Acceptance of existing channel members

Table 2. Importance Weights of Different Criteria during the NPD Process

	Phase of Design Process[1]				
Criteria	**1**	**2**	**3**	**4**	**5**
Product	34	45	52	36	24
Exclusivity					
Performance/Feasibility					
Ease of Service					
Legality					
Organizational Support					
Safety					
Market	51	30	19	24	30
Size					
Growth rate					
Relation to present product lines					
Expected competitive situation					
Distribution characteristics					
Special political and social factors					
Financial	15	25	29	40	46
ROI					
Effect on cash flow					
Total investment requirement					
Payback					
Total Points	100	100	100	100	100

[1]
Phase 1	Concept Phase
Phase 2	Feasibility Phase
Phase 3	Product/Process Phase
Phase 4	Scale-Up Phase
Phase 5	Standardization Phase

Table 3. Suggested Causes of New Product Failure

Reason for Failure	Elaboration
Market too small	Insufficient demand for the product
Poor match for company/ company requirements	Company capabilities do not match needs of product
Lack of significant advantages	Product lacks a significant price or performance advantage over existing products
Lack of channel support for product	Channel members unwilling or unable to support product
Changes in consumers' tastes	Consumer preferences shifted before or during product launch
Competitive entry into market	Compeitive product entered market
Not new/not different	Poor idea that offers nothing new
Poor positioning	Perceived attributes of product are not unique or superior
Forecasting error	Overestimation of sales potential
Insufficient return on investment	Poor profit margins and/or high costs
Changes in environmental constraints	Drastic change in key environmental factor
Organizational problems	Interorganizational conflicts and poor management practices

Table 4. Results of Selected Studies on Factors Related to New Product Success

Author	Type of Industry	Respondents	Sample Size	Factors Related to New Product Success/Failure
Link (1987)	Australian industrial manufacturers	Marketing managers	135 firms	1. Management of launch execution 2. Synergy with existing business 3. Completeness of market intelligence 4. Product/market attractiveness 5. Product novelty (uniqueness) 6. Product quality
Cooper (1978)	Canadian industrial products	Top managers	103 firms	1. Product uniqueness/superiority 2. Market knowledge/marketing proficiency 3. Technical/production synergy and proficiency 4. Market dynamism 5. Market size, need, and growth rate 6. Relative price of product 7. Synergy with managerial and marketing resources 8. Market competitiveness and customer satisfaction 9. Newness of product to firm 10. Strength of marketing communications and launch effort 11. Source of idea/investment magnitude
Zirger and Maidique (1990)	US equip't manufacturers	Top managers	86 firms	1. Excellence in R&D organization 2. Superior technical performance 3. Product value 4. Synergy with existing competencies 5. Management support 6. Competence of marketing and manufacturing 7. Weakness of the competitive market 8. Market size and growth rate

Table 4, Cont'd.

Author	Type of Industry	Respondents	Sample Size	Factors Related to New Product Success/Failure
Cooper and de Brentani (1991)	Industrial financial services	Senior managers	37 firms	1. Synergy with firm's skills and resources 2. Product/market fit 3. Quality of launch execution 4. Product uniqueness/superiority 5. Quality of execution of marketing activities 6. Market size and growth 7. Service expertise 8. Quality of execution of technical activities 9. Quality of service delivery 10. Quality of execution of predevelopment activities 11. Tangible evidence

Table 5. Results of Cooper's (1978) Discriminant Analysis

Factor Name	Standardized Function Coefficients	Wilks' Lambda[1]
Product Uniqueness/Superiority	0.527	0.859
Market Knowledge and Marketing Proficiency	0.465	0.730
Technical/Production Synergy and Proficiency	0.325	0.680
Market Dynamism	-0.264	0.644
Market Need, Growth, & Size	0.271	0.610
Relative Price of Product	-0.252	0.576
Marketing and Managerial Synergy	0.193	0.557
Marketing Competitiveness and Customer Satisfaction	-0.186	0.540
Newness to the Firm	-0.170	0.526
Strength of Marketing Communications and Launch Effort	0.137	0.517
Source of Idea/Investment Magnitude	0.114	0.510

Group Centroids

Successes	0.666
Failures	-0.731

[1]All values of Wilks' Lambda significant at the 0.001 level.

Table 6. Hypotheses

H1:	Attributions of new product success/failure to some factor will increase the perceived diagnosticity of information about that factor.
H2:	The perceived diagnosticity of an item of information for success or failure will be positively related to the probability of the information being acquired and negatively related to the order of its acquisition.
H3:	The decision maker's level of experience will be positively related to the number of attributions made for new product success and failure.
H4:	Experience will affect the specific attributions made for new product success and failure.
H5:	Experience will affect the perceived diagnosticity of information for new product success and failure.
H6:	Experience will be positively related to the number of items of information acquired during the evaluation of new product concepts.
H7:	Experience will be related to the consistency between the order of search for information and the perceived diagnosticity of information.
H8:	Experience will be related to the specific choice of information items gathered during evaluation.
H9:	Experience will be related to the amount of time spent in search.
H10:	Experience will be negatively related to the use of cutoffs.
H11:	Experience will be positively related to the use of cutoffs used and on the severity of the cutoffs used on different criteria.
H12:	Experience will be related to the evaluations of new product concepts.

Table 7. Average Diagnosticity Ratings Using Three Measures of Diagnosticity

	Item	Measure 1	Measure 2	Measure 3
1	Amount of management's experience with product market	7.2	7.0	6.9
2	Ability to use existing sales force	6.0	6.1	5.8
3	Market size	6.7	6.9	6.0
4	Market growth rate	7.2	6.7	6.6
5	Whether company can use current production processes	6.4	6.6	5.8
6	Whether costs drop with volume sold	6.0	6.0	5.7
7	Level of seasonal/cyclical fluctuations in demand	6.0	5.7	5.1
8	Whether product offers a meaningful advantage to users	8.0	8.1	7.4
9	Likelihood of competitive retaliation against product	7.4	7.4	6.6
10	Speed of change of technology in the product-market	7.3	7.1	6.4
11	Level of support from distributors	6.9	6.9	6.6
12	Level of product's differentiation from the competition	7.6	7.8	7.5
13	Source of product idea (internal or external)	3.7	4.0	4.5
14	Product's quality compared to competition	8.0	8.0	7.5

Table 7, cont'd.

	Item	Measure 1	Measure 2	Measure 3
15	Focus group's evaluation of the concept	6.6	6.6	6.1
16	Colleague's opinions of the product	5.0	5.2	5.4
17	Number of other products in development	5.0	5.2	5.0
18	Time from concept approval to introduction of product	5.8	5.8	5.4
19	Whether product is patentable	6.5	6.8	6.0
20	Projected market share	7.0	7.1	6.7

Table 8. Correlations between different measures of diagnosticity

	Item	$R_{1,2}$	$R_{1,3}$	$R_{2,3}$
1	Amount of management's experience with product market	0.82	0.49	0.60
2	Ability to use existing sales force	0.73	0.42	0.56
3	Market size	0.76	0.31*	0.26*
4	Market growth rate	0.68	0.49	0.60
5	Whether company can use current production processes	0.44	0.72	0.42
6	Whether costs drop with volume sold	0.47	0.47	0.41
7	Level of seasonal/cyclical fluctuations in demand	0.65	0.24*	0.47
8	Whether product offers a meaningful advantage to users	0.55	0.30*	0.11*
9	Likelihood of competitive retaliation against product	0.80	0.35*	0.26*
10	Speed of change of technology in the product-market	0.56	0.33*	0.41
11	Level of support from distributors	0.60	0.40	0.53
12	Level of product's differentiation from the competition	0.58	0.46	0.19*
13	Source of product idea (internal or external)	0.79	0.46	0.51
14	Product's quality compared to competition	0.64	0.64	0.39
15	Focus group's evaluation of the concept	0.86	0.48	0.52
16	Colleague's opinions of the product	0.63	0.38	0.35*
17	Number of other products in development	0.77	0.43	0.52
18	Time from concept approval to introduction of product	0.63	0.47	0.61
19	Whether product is patentable	0.69	0.18*	0.35*
20	Projected market share	0.50	0.21*	0.33*
	Average	0.66	0.41	0.42

* = Not significant

Table 9. Information Items Used in the Questionnaire

Item Number	Information
1	Demand made on company's financial resources
2	Extent of company's experience w/necessary technology
3	Amount of management's experience w/product and market
4	Extent of changes needed in distribution system
5	Ability to use existing sales force
6	Likely effect on sales of existing product
7	Whether existing supply channels can be used
8	Market size
9	Market growth rate
10	Whether company can use current production processes
11	Whether costs drop with volume sold
12	Level of seasonal/cyclical fluctuations in demand
13	Market entry costs
14	Whether competition is vulnerable
15	Whether product offers a meaningful advantage to users
16	Strength of existing competitors
17	Strength of potential competitors not yet in market
18	Likelihood of new competitive entry into the market
19	Likelihood of competitive retaliation against product
20	Speed of change in technology in the product-market
21	Level of support from distributors
22	Level of product's differentiation from competitors
23	Likely price position relative to competition
24	Source of product idea (internal or external)

Table 9, cont'd.

Item Number	Information
25	Product's quality compared to competition
26	Level of upper management support for the product
27	Focus group's evaluation of the concept
28	Colleagues' opinions of the product
29	Salespeople's opinions of the product
30	Number of other products in development
31	Time from concept approval to introduction of product
32	Whether consumers must change their methods of use
33	Number of major competitors
34	Whether product is patentable or can be legally protected
35	Projected market share
36	Likelihood of adverse government regulation
37	Results of quantitative analyses of consumer preference
38	Extent of behavior change needed for product use

Table 10. Descriptive Statistics

Industry Breakdown

Industry	Number of respondents	Percentage
Pharmaceutical	34	54.8
Software	28	45.2
Total	62	100.0

Where experience was obtained

Where experience was obtained	Number of Respondents	Percentage
A former position	3	4.8
Current position	12	19.4
Both former and current positions	46	74.2
No experience	1	1.6
Total	62	100.0

Current role in the evaluation of new product concepts

Role in evaluation	Number of Respondents	Percentage
Primary decision maker	17	27.4
Give major input to primary decision maker	32	51.6
Give some input to primary decision maker	9	14.5
No role in evaluation	0	0.0
Missing	4	6.5
Total	62	100.0

Table 10, cont'd.

Former role in the evaluation of new product concepts

Role in evaluation	Number of Respondents	Percentage
Primary decision maker	6	9.7
Give major input to primary decision maker	22	35.5
Give some input to primary decision maker	18	29.0
No role in evaluation	3	4.8
Missing	13	21.0
Total	62	100.0

Functional background

Functional background	Number of respondents	Percentage
Accounting	1	1.6
Engineering	3	4.8
Finance	1	1.6
Marketing	25	40.3
Production/Operations Management	5	8.1
Research and development	12	19.4
Other	13	21.0
Missing	2	3.2
Total	62	100.0

Table 10, cont'd.

Educational background

Educational background	N	Percentage
Business	29	46.8
Computer science	7	11.3
Engineering	4	6.5
Humanities/Liberal arts	3	4.8
Medicine	1	1.6
Mathematics	1	1.6
Physical sciences	6	9.7
Social sciences	1	1.6
Other	6	9.7
Missing	4	6.5
Total	62	100.0

Educational level

Educational level	N	Percentage
Attended high school, but did not finish	1	1.6
Finished high school	0	0.0
Some college	2	3.2
College graduate	14	22.6
Some postgraduate coursework	9	14.5
Master's degree	27	43.6
Ph.D.	6	9.7
Other	1	1.6
Missing	2	3.2
Total	62	100.0

Table 10, cont'd.

Age

Age	Number of respondents	Percentage
Under 22	0	0.0
22-30	6	9.7
31-40	26	41.9
41-50	20	32.3
51-60	7	11.3
61-65	1	1.6
66 and over	0	0.0
Missing	2	3.2
Total	62	100.0

Gender

Gender	Number of respondents	Percentage
Male	47	75.8
Female	13	21.0
Missing	2	3.2
Total	62	100.0

Table 11. Coding Scheme for Success and Failure Attributions

Code	Topic
1	Demand made on company's financial resources
2	Company's experience with necessary technology
3	Management's experience with product and market
4	Distribution system
5	Sales force issues
6	Effect on sales of existing products
7	Supply channels
8	Market size
9	Market growth rate
10	Use current production processes
11	Product cost issues
12	Strength or stability of demand
13	Market entry costs
14	Vulnerability of competition
15	Whether product offers a meaningful advantage to users
16	Strength of existing competitors
17	Strength of potential competitors not yet in market
18	New competitive entry into market
19	Competitive retaliation against product
20	Speed of change in technology in the product-market
21	Distributor support
22	Product's differentiation from competitors (uniqueness, positioning, superiority)
23	Pricing issues
24	Source of product idea (internal or external)

Table 11, cont'd.

Code	Topic
25	Product's quality (compared to competition and other quality issues)
26	Upper management support for the product
27	Focus group's evaluation of the product
28	Colleague's opinions of the product
29	Salespeople's opinions of the product
30	Number of other products in development
31	Development time
32	Change in consumers' methods of use
33	Number of major competitors
34	Ability to protect product (patentability)
35	Projected market share
36	Government regulation
37	Quantitative analyses of consumer preference
38	Change in behavior needed for use
39	Appeals to press/gets PR, word-of-mouth
40	Consistency with consumer's expectations of product or company
41	Product or company image, reputation
42	Impact on company's earnings
43	Value, cost effectiveness
44	Timing of market entry
45	Ability to meet firm's financial goals (perhaps in specified time period)
46	Adequacy of market targeting
47	Level and/or adequacy of marketing support
48	Product's ability to deliver on promises made

Table 11, cont'd.

Code	Topic
49	Management competence
50	Adequacy of product design
51	Adequacy of market research
52	Adequacy of product testing
53	Adequacy of launch
54	Field support, customer service issues
55	Pharmaceutical specific issues
56	Ease of use
57	Product extensibility/ability to change with customers needs
58	Level of consumer satisfaction with existing products
59	Innovativeness, innovation
60	Ease of explaining benefits to consumer/marketability
61	Proficiency of new product development process (including setting goals, screening, financial planning, interfunctional coordination)
62	Customer acceptance, loyalty
63	Fit between company's strengths & plans and product/market needs
64	Product line issues
65	Political/social reasons for pursuing product ("product champion", "falling in love")
66	Customer feedback used in design, marketing
67	Product sharpness, polish, packaging, shelf presence
68	Economic, political, technological environment
69	Market penetration/category penetration
70	Other market characteristics (besides size and growth rate)
71	Technological problems

Table 11, cont'd.

Code	Topic
72	Development risk
73	Company culture, internal environment
74	Product performance, effectiveness
75	Software specific issues

Table 12. Mean Number of Attributions for Success and Failure

	All Respondents (N = 62)		Pharmaceutical Respondents (N = 34)		Software Respondents (N = 28)	
Attributions for	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Success	4.77	2.27	4.94	2.47	4.57	2.03
Failure	5.13	3.00	5.65	3.15	4.50	2.73
Total Attributions	9.90	4.47	10.59	4.72	9.07	4.07

Table 13. **Attributions Ranked by Percent Mentioning as a Cause of Product Success**

Code	Attribution	Percent Mentioning
15	Whether product offers a meaningful advantage to users	67.7
22	Product's differentiation from competitors (uniqueness, positioning, superiority)	32.3
47	Level and/or adequacy of marketing support	24.2
23	Pricing issues	24.2
43	Value, cost effectiveness	21.0
56	Ease of use	16.1
44	Timing of market entry	14.5
4	Distribution system	14.5
45	Ability to meet firm's financial goals (perhaps in specified time period)	14.5
41	Product or company image, reputation	12.9
1	Demand made on company's financial resources	11.3
34	Ability to protect product (patentability)	11.3
62	Customer acceptance, loyalty	9.7
59	Innovativeness, innovation	9.7
40	Consistency with consumer's expectations of product or company	8.1
8	Market size	8.1
11	Product cost issues	8.1
42	Impact on company's earnings	8.1
25	Product's quality (compared to competition and other quality issues)	6.5

Table 13, cont'd.

Code	Attribution	Percent Mentioning
61	Proficiency of new product development process (including setting goals, screening, financial planning, interfunctional coordination	6.5
55	Pharmaceutical specific issues	6.5
50	Adequacy of product design	6.5
46	Adequacy of market targeting	6.5
60	Ease of explaining benefits to consumer/marketability	6.5
39	Appeals to press/gets PR, word-of-mouth	6.5
67	Product sharpness, polish, packaging, shelf presence	6.5
5	Sales force issues	6.5
18	New competitive entry into market	6.5
64	Product line issues	6.5
33	Number of major competitors	4.8
3	Management's experience with product and market	4.8
58	Level of consumer satisfaction with existing products	4.8
57	Product extensibility/ability to change with customers needs	4.8
9	Market growth rate	4.8
6	Effect on sales of existing products	4.8
51	Adequacy of market research	3.2
31	Development time	3.2
16	Strength of existing competitors	3.2
54	Field support, customer service issues	3.2
14	Vulnerability of competition	3.2

Table 13, cont'd.

Code	Attribution	Percent Mentioning
10	Use current production processes	3.2
26	Upper management support for the product	3.2
2	Company's experience with necessary technology	3.2
74	Product performance, effectiveness	3.2
12	Strength or stability of demand	3.2
66	Customer feedback used in design, marketing	3.2
63	Fit between company's strengths & plans and product/market needs	3.2
69	Market penetration/category penetration	3.2
19	Competitive retaliation against product	1.6
70	Other market characteristics (besides size and growth rate)	1.6
52	Adequacy of product testing	1.6
35	Projected market share	1.6
38	Change in behavior needed for use	1.6
21	Distributor support	1.6
73	Company culture, internal environment	1.6
75	Software specific issues	1.6
13	Market entry costs	1.6
72	Development risk	1.6
32	Change in consumers' methods of use	1.6
48	Product's ability to deliver on promises made	1.6
65	Political/social reasons for pursuing product ("product champion", "falling in love")	0.0
49	Management competence	0.0

Table 13, cont'd.

Code	Attribution	Percent Mentioning
20	Speed of change in technology in the product-market	0.0
68	Economic, political, technological environment	0.0
53	Adequacy of launch	0.0
7	Supply channels	0.0
71	Technological problems	0.0
17	Strength of potential competitors not yet in market	0.0
27	Focus group's evaluation of the product	0.0
37	Quantitative analyses of consumer preference	0.0
30	Number of other products in development	0.0
36	Government regulation	0.0
24	Source of product idea (internal or external)	0.0
28	Colleague's opinions of the product	0.0
29	Salespeople's opinions of the product	0.0

Table 14. Attributions Ranked by Percent Mentioning as a Cause of Product Failure

Code	Attribution	Percent Mentioning
47	Level and/or adequacy of marketing support	43.5
15	Whether product offers a meaningful advantage to users	38.7
51	Adequacy of market research	25.8
23	Pricing issues	24.2
22	Product's differentiation from competitors (uniqueness, positioning, superiority)	22.6
1	Demand made on company's financial resources	19.4
61	Proficiency of new product development process (including setting goals, screening, financial planning, interfunctional coordination	17.7
25	Product's quality (compared to competition and other quality issues)	17.7
44	Timing of market entry	16.1
40	Consistency with consumer's expectations of product or company	14.5
31	Development time	14.5
19	Competitive retaliation against product	14.5
4	Distribution system	11.3
33	Number of major competitors	11.3
43	Value, cost effectiveness	9.7
55	Pharmaceutical specific issues	9.7
16	Strength of existing competitors	9.7
65	Political/social reasons for pursuing product ("product champion", "falling in love")	9.7
56	Ease of use	8.1

Table 14, cont'd.

Code	Attribution	Percent Mentioning
45	Ability to meet firm's financial goals (perhaps in specified time period)	8.1
8	Market size	8.1
60	Ease of explaining benefits to consumer/marketability	8.1
46	Adequacy of market targeting	8.1
50	Adequacy of product design	8.1
3	Management's experience with product and market	8.1
11	Product cost issues	6.5
5	Sales force issues	6.5
39	Appeals to press/gets PR, word-of-mouth	6.5
67	Product sharpness, polish, packaging, shelf presence	6.5
14	Vulnerability of competition	6.5
54	Field support, customer service issues	6.5
26	Upper management support for the product	6.5
10	Use current production processes	6.5
50	Management competence	6.5
20	Speed of change in technology in the product-market	6.5
2	Company's experience with necessary technology	4.8
42	Impact on company's earnings	3.2
18	New competitive entry into market	3.2
12	Strength or stability of demand	3.2
74	Product performance, effectiveness	3.2
52	Adequacy of product testing	3.2

Table 14, cont'd.

Code	Attribution	Percent Mentioning
70	Other market characteristics (besides size and growth rate)	3.2
35	Projected market share	3.2
21	Distributor support	3.2
38	Change in behavior needed for use	3.2
68	Economic, political, technological environment	3.2
53	Adequacy of launch	3.2
71	Technological problems	3.2
7	Supply channels	3.2
57	Product extensibility/ability to change with customers needs	1.6
58	Level of consumer satisfaction with existing products	1.6
9	Market growth rate	1.6
66	Customer feedback used in design, marketing	1.6
75	Software specific issues	1.6
73	Company culture, internal environment	1.6
27	Focus group's evaluation of the product	1.6
17	Strength of potential competitors not yet in market	1.6
37	Quantitative analyses of consumer preference	1.6
41	Product or company image, reputation	0.0
34	Ability to protect product (patentability)	0.0
62	Customer acceptance, loyalty	0.0
59	Innovativeness, innovation	0.0
64	Product line issues	0.0

Table 14, cont'd.

Code	Attribution	Percent Mentioning
6	Effect on sales of existing products	0.0
63	Fit between company's strengths & plans and product/market needs	0.0
69	Market penetration/category penetration	0.0
72	Development risk	0.0
13	Market entry costs	0.0
48	Product's ability to deliver on promises made	0.0
32	Change in consumers' methods of use	0.0
28	Colleague's opinions of the product	0.0
29	Salespeople's opinions of the product	0.0
24	Source of product idea (internal or external)	0.0
30	Number of other products in development	0.0
36	Government regulation	0.0

Table 15. Crosstabulations on Attributions by Industry[1]

Industry	Success attributed to **positive effect on sales of existing products** No	Success attributed to **positive effect on sales of existing products** Yes	TOTAL
Pharmaceutical	34 (32.4)	0 (1.6)	34
Software	25 (26.6)	3 (1.4)	28
TOTAL	59	3	62

X^2 with 1 df = 3.83, p = 0.05

Industry	Success attributed to **product cost issues** No	Success attributed to **product cost issues** Yes	TOTAL
Pharmaceutical	29 (31.3)	5 (2.7)	34
Software	28 (25.7)	0 (2.2)	28
TOTAL	57	5	62

X^2 with 1 df =4.48 , p = 0.03

[1]Please note that the expected cell frequency is in ( ) below the actual frequency.

Table 15, cont'd.

Industry	Success attributed to **the ability to legally protect the product**		TOTAL
	No	Yes	
Pharmaceutical	27 (30.2)	7 (3.8)	34
Software	28 (24.8)	0 (3.16)	28
TOTAL	55	7	62

X^2 with 1 df = 6.50, p = 0.01

Industry	Success attributed to **product's ability to attract press, get PR**		TOTAL
	No	Yes	
Pharmaceutical	34 (31.8)	0	34
Software	24 (26.2)	4 (1.8)	28
TOTAL	58	4	62

X^2 with 1 df = 5.19, p = 0.02

Industry	Success attributed to **product line issues**		TOTAL
	No	Yes	
Pharmaceutical	34 (31.8)	0	34
Software	24 (26.2)	4 (1.8)	28
TOTAL	58	4	62

X^2 with 1 df = 3.52, p = 0.06

Table 15, cont'd.

Industry	Failure attributed to **factors related to production process**		TOTAL
	No	Yes	
Pharmaceutical	30 (31.8)	4 (2.2)	34
Software	28 (26.2)	0 (1.8)	28
TOTAL	58	4	62

X^2 with 1 df = 3.52, p = 0.06

Industry	Failure attributed to **factors related to product cost**		TOTAL
	No	Yes	
Pharmaceutical	30 (31.8)	4 (2.2)	34
Software	28 (26.2)	0 (1.8)	28
TOTAL	58	4	62

X^2 with 1 df = 3.52, p = 0.06

Industry	Failure attributed to **pricing issues**		TOTAL
	No	Yes	
Pharmaceutical	22 (25.8)	12 (8.2)	34
Software	25 (21.2)	3 (6.8)	28
TOTAL	47	15	62

X^2 with 1 df = 5.06, p = 0.02

Table 15, cont'd.

Industry	Failure attributed to **product's quality**		TOTAL
	No	Yes	
Pharmaceutical	31 (28.0)	3 (6.0)	34
Software	20 (23.0)	8 (5.0)	28
TOTAL	51	11	62

X^2 with 1 df = 4.10, p = 0.04

Industry	Failure attributed to **the number of competitors**		TOTAL
	No	Yes	
Pharmaceutical	28 (30.2)	6 (3.8)	34
Software	27 (24.8)	1 (3.2)	28
TOTAL	55	7	62

X^2 with 1 df = 3.04, p = 0.08

Industry	Failure attributed to **the timing of market entry**		TOTAL
	No	Yes	
Pharmaceutical	25 (28.5)	9 (5.5)	34
Software	27 (23.5)	1 (4.5)	28
TOTAL	52	10	62

X^2 with 1 df = 6.0, p = 0.02

Table 15, cont'd.

Industry	Failure attributed to **field support, customer service issues**		TOTAL
	No	Yes	
Pharmaceutical	34 (31.8)	0 (2.2)	34
Software	24 (26.2)	4 (1.8)	28
TOTAL	58	4	62

X^2 with 1 df = 5.2, p = 0.02

Table 16. Mean Diagnosticity Ratings of Information Items
(Mean of all respondents)

Information Item	Mean Diagnosticity	Std. Dev.
Whether product offers a meaningful advantage to users	8.2	1.2
Level of product's differentiation from competitors	7.8	1.3
Product's quality compared to competition	7.8	1.1
Market size	7.5	1.3
Strength of existing competitors	7.5	1.4
Level of upper management support for the product	7.5	1.9
Whether consumers must change their methods of use	7.4	1.6
Extent of behavior change needed for product use	7.3	1.8
Number of major competitors	7.3	1.7
Likelihood of adverse government regulation	7.2	2.2
Time from concept approval to introduction of product	7.2	1.5
Whether competition is vulnerable	7.2	1.7
Likely price position relative to competition	7.2	1.6
Speed of change in technology in the product-market	7.1	1.7
Market entry costs	7.1	1.5
Extent of company's experience w/necessary technology	7.1	1.5
Demand made on company's financial resources	7.1	1.8
Results of quantitative analyses of consumer preference	6.9	1.8
Projected market share	6.9	1.8
Amount of management's experience w/product and market	6.8	1.7
Ability to use existing sales force	6.8	1.9
Whether existing supply channels can be used	6.8	2.0

Table 16, cont'd.

Information Item	Mean Diagnosticity	Std. Dev.
Market growth rate	6.7	1.3
Salespeople's opinions of the product	6.6	1.7
Level of support from distributors	6.6	1.8
Likelihood of new competitive entry into the market	6.5	1.8
Whether company can use current production processes	6.4	2.0
Whether product is patentable or can be legally protected	6.3	2.2
Strength of potential competitors not yet in market	6.2	2.0
Likelihood of competitive retaliation against product	6.2	2.0
Focus group's evaluation of the concept	6.1	2.0
Extent of changes needed in distribution system	6.1	1.8
Likely effect on sales of existing product	6.1	2.2
Number of other products in development	5.7	2.2
Whether costs drop with volume sold	5.4	2.2
Colleagues' opinions of the product	5.2	2.2
Level of seasonal/cyclical fluctuations in demand	4.6	2.4
Source of product idea (internal or external)	2.7	2.1

Table 17. Results of T-tests on Mean Diagnosticity Ratings by Industry

Information Item	Means for Pharmaceutical Respondents	Means for Software Respondents	t	p	Effect Size, d
Market growth rate	7.18	6.21	2.39	0.02	0.61
Whether costs drop with volume sold	5.97	4.71	2.29	0.03	0.60
Level of seasonal/cyclical fluctuations in demand	5.09	4.07	1.67	0.10	0.43
Likelihood of new competitive entry into market	6.85	6.11	1.68	0.10	0.43
Salespeople's opinions of the product	6.06	7.32	-3.05	0.00	0.79
Whether product is patentable	6.94	5.46	2.83	0.01	0.72
Projected market share	7.26	6.43	1.82	0.07	0.46
Likelihood of adverse government regulation	7.91	6.39	2.69	0.01	0.79

Table 18. Mean Diagnosticity Ratings of Different Groups of Information

Group	Items Making Up Group	Mean Diagnosticity Rating	Std. Dev.
8. Product factors	• Whether product offers meaningful advantage to users • Level of product's differentiation from competitors • Likely price position relative to competition • Product's quality compared to competition	7.75	0.85
9. Social/political factors	• Level of upper management support for the product	7.47	1.86
7. Risk	• Speed of change in technology in the product-market • Level of support from distributors • Whether consumers must change their methods of use • Likelihood of adverse government regulation • Extent of behavior change needed for product use • Whether product is patentable or can be legally protected	7.00	1.27
1. Match to organizational goals and capabilities	• Demand made on company's financial resources • Extent of company's experience with necessary technology • Amount of management's experience with product and market • Whether company can use current production processes	6.84	1.12

Table 18, cont'd.

Group	Items Making Up Group	Mean Diagnosticity Rating	Std. Dev.
5. Competitive factors	• Strength of existing competitors • Strength of potential competitors not yet in market • Likelihood of new competitive entry into the market • Likelihood of competitive retaliation against product • Number of major competitors • Whether competition is vulnerable	6.81	1.24
12. Outcome of consumer research	• Focus group's evaluation of the concept • Results of quantitative analyses of consumer preference	6.52	1.51
11. New product development process	• Number of other products in development • Time from concept approval to product introduction	6.44	1.41
2. Match to existing products or product lines	• Extent of changes needed in distribution system • Ability to use existing salesforce • Likely effect on sales of existing products • Whether existing supply channels can be used	6.44	1.42
3. Market characteristics	• Market size • Market growth rate • Whether costs drop with volume sold • Level of seasonal/cyclical fluctuations in demand • Market entry costs • Projected market share	6.38	1.08

Table 18, cont'd.

Group	Items Making Up Group	Mean Diagnosticity Rating	Std. Dev.
10. Opinions of others	• Colleagues' opinions of the product • Salespeople's opinions of the product	5.90	1.58
13. Source of product idea	• Source of product idea (internal or external)	2.74	2.08

Results of paired t-tests on mean diagnosticity ratings of groups of information items:

Group:	8	9	7	1	5	12	11	2	3	10	13
Means:	7.75	7.47	7.00	6.84	6.81	6.52	6.44	6.44	6.38	5.90	2.74

Table 19. Means of Expertise and Experience Measures

Means of Continuous Measures

Variables	All Respondents (N = 62)		Pharmaceutical Respondents (N = 34)		Software Respondents (N = 28)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Perceived knowledge	6.11	1.80	6.26	1.69	5.93	1.94
Perceived expertise	6.02	1.95	6.09	1.86	5.93	2.09
Industry tenure (years)	11.62	7.28	12.95	7.34	10.00	6.98
Tenure in new product development (years)	8.52	7.72	9.18	8.51	7.71	6.70
Number of new product decisions involved in	31.11	40.91	31.5	37.92	30.64	44.98

Table 19, cont'd.

Frequencies for the frequency of seeking advice from others when evaluating new product concepts

All Respondents

Frequency of seeking advice	Frequency	Percent
Almost never seek advice	2	3.2
Occasionally seek advice	6	9.7
Frequently seek advice	20	32.3
Almost always seek advice	34	54.8
TOTAL	62	100.0

Pharmaceutical respondents

Frequency of seeking advice	Frequency	Percent
Almost never seek advice	2	5.9
Occasionally seek advice	4	11.8
Frequently seek advice	14	41.2
Almost always seek advice	14	41.2
TOTAL	34	100.0

Software respondents

Frequency of seeking advice	Frequency	Percent
Almost never seek advice	0	0.0
Occasionally seek advice	2	7.1
Frequently seek advice	6	21.4
Almost always seek advice	20	71.4
TOTAL	28	100.0

Table 20. Correlations Among Expertise and Experience Measures

All Respondents

	Perceived Knowledge	Advice Seeking	Perceived Expertise	Tenure in NPD	Number of New Product Decisions	Industry Tenure
Perceived Knowledge	1.00					
Frequency of Seeking Advice	0.21	1.00				
Perceived Expertise	0.93[1]	0.18	1.00			
Tenure in NPD	0.24[4]	-0.07	0.26[4]	1.00		
Number of New Product Decisions	0.36[3]	0.06	0.37[3]	0.55[1]	1.00	
Industry Tenure	0.12	0.06	0.08	0.64[1]	0.42[2]	1.00

[1] $p \leq 0.0001$
[2] $p \leq 0.001$
[3] $p \leq 0.01$
[4] $p \leq 0.10$

Table 21. Factor Loadings of the Experience and Expertise Measures

Rotated Factor Matrix:

Variable	Loading on Factor 1	Loading on Factor 2
Tenure in NPD	0.90	
Industry tenure	0.84	
Number of new product decisions	0.73	
Perceived knowledge		0.93
Perceived expertise		0.93
Frequency of seeking advice		0.43

Final Statistics:

Factor	Eigenvalue	Percent of Variance Explained
1	2.62	43.8
2	1.53	25.6
TOTAL		69.4

Table 22. Reliability Analysis of the Expertise and Experience Variables

Scale: EXPERTISE
Variables: Perceived knowledge, Frequency of seeking advice, and Perceived expertise
Cronbach's α = 0.70

Variable	Item-to-Total Correlation	Alpha if item deleted
Perceived knowledge	0.74	0.31
Frequency of seeking advice	0.20	0.96
Perceived expertise	0.72	0.35

Scale: EXPERIENCE
Variables: Tenure in NPD, Industry tenure, and the Number of new product decisions
Cronbach's α = 0.78

Variable	Item-to-Total Correlation	Alpha if item deleted
Tenure in NPD	0.71	0.59
Industry tenure	0.53	0.78
Number of new product decisions	0.60	0.71

Table 23. Results of Paired T-test on Diagnosticity Ratings on Attributions Made vs. Attributions not Made

Success Attributions	Mean Diagnosticity Rating	Standard Deviation
Items for which attributions were made	7.72	1.16
Items for which attributions were not made	6.61	0.86
Difference	1.11	1.26

Test that mean difference is equal to 0:
$t_{57} = 6.76$, $p = 0.0001$

Failure Attributions	Mean Diagnosticity Rating	Standard Deviation
Items for which attributions were made	7.77	1.02
Items for which attributions were not made	6.59	0.85
Difference	1.17	1.16

Test that mean difference is equal to 0:
$t_{55} = 7.59$, $p = 0.0001$

Table 23, cont'd.

Results of Paired T-test on Diagnosticity Ratings on Attributions Made vs. Attributions not Made Excluding Items with Lowest Diagnosticity

Success Attributions	Mean Diagnosticity Rating	Standard Deviation
Items for which attributions were made	7.73	1.16
Items for which attributions were not made	6.79	0.86
Difference	0.94	1.26

Test that mean difference is equal to 0:
$t_{57} = 5.76$, $p = 0.0001$

Failure Attributions	Mean Diagnosticity Rating	Standard Deviation
Items for which attributions were made	7.81	1.01
Items for which attributions were not made	6.77	0.85
Difference	1.04	1.14

Test that mean difference is equal to 0:
$t_{55} = 6.91$, $p = 0.0001$

Table 24. Mean Number of Items Searched for Each Concept

Concept	Mean Number of Items Searched	Std. Dev.
Good	6.90	3.23
Bad	5.47	3.39
Mixed	6.15	3.36
Total searched for all concepts	18.20	8.43

Repeated measures t-tests on difference in number of items searched for each concept

Difference between	Difference	Std. Dev.	t	p
Good vs. Bad	1.39	3.17	3.32	0.002
Bad vs. Mixed	-0.56	2.76	-1.56	0.12
Mixed vs. Good	-0.81	3.13	-1.97	0.05

Table 25. Correlation Between Likelihood of Information Being Selected and Diagnosticity Ratings

All Respondents

Concept	Correlation between Item Selection and Diagnosticity Rating	p-value
Good	0.34	0.0001
Bad	0.30	0.0001
Mixed	0.33	0.0001

Pharmaceutical Respondents

Concept	Correlation between Item Selection and Diagnosticity Rating	p-value
Good	0.35	0.0001
Bad	0.29	0.0001
Mixed	0.35	0.0001

Software Respondents

Concept	Correlation between Item Selection and Diagnosticity Rating	p-value
Good	0.33	0.0001
Bad	0.30	0.0001
Mixed	0.33	0.0001

Table 26. Correlation Between Order of Search and Diagnosticity Ratings

All Respondents

Concept	Correlation between order of search and diagnosticity rating	p-value
Good	-0.38	0.0001
Bad	-0.27	0.0001
Mixed	-0.35	0.0001

Pharmaceutical Respondents

Concept	Correlation between order of search and diagnosticity rating	p-value
Good	-0.35	0.0001
Bad	-0.29	0.0001
Mixed	-0.34	0.0001

Software Respondents

Concept	Correlation between order of search and diagnosticity rating	p-value
Good	-0.42	0.0001
Bad	-0.25	0.0001
Mixed	-0.38	0.0001

Table 27. Correlations between Number of Attributions and Experience and Expertise

	Experience	Expertise
Number of Success Attributions	0.02	0.08
Number of Failure Attributions	-0.09	0.01
Total Number of Attributions	-0.05	0.05

Table 28. Results of Regressing Attributions on Experience and Expertise

	β_1Expertise	β_2Experience	- 2 Log Likelihood (df = 2)	p
Success Attributions	-0.02	0.00	0.51	0.77
Failure Attributions	0.04	-0.02	1.21	0.55

Table 29. Correlations between Diagnosticity Ratings and Measures of Expertise and Experience

Information Item	Correlation with EXPERTISE	p	Correlation with EXPERIENCE	p
Demand made on company's financial resources	-0.24	0.06	0.08	0.53
Extent of company's experience w/necessary technology	-0.14	0.29	0.29	0.02
Amount of management's experience w/product and market	-0.00	0.99	0.21	0.11
Extent of changes needed in distribution system	0.09	0.47	0.14	0.28
Ability to use existing sales force	-0.07	0.60	0.02	0.86
Likely effect on sales of existing product	-0.15	0.25	0.07	0.59
Whether existing supply channels can be used	-0.12	0.34	0.25	0.05
Market size	-0.17	0.18	-0.06	0.65
Market growth rate	-0.14	0.29	0.07	0.55
Whether company can use current production processes	-0.27	0.03	0.04	0.78
Whether costs drop with volume sold	-0.14	0.27	-0.02	0.87
Level of seasonal/cyclical fluctuations in demand	-0.55	0.08	0.01	0.95
Market entry costs	-0.05	0.68	0.07	0.60
Whether competition is vulnerable	-0.08	0.56	0.19	0.14

Table 29, cont'd.

Information Item	Correlation with EXPERTISE	p	Correlation with EXPERIENCE	p
Whether product offers a meaningful advantage to users	0.03	0.82	0.06	0.64
Strength of existing competitors	0.06	0.64	0.11	0.40
Strength of potential competitors not yet in market	-0.24	0.06	-0.04	0.75
Likelihood of new competitive entry into the market	-0.11	0.39	-0.06	0.64
Likelihood of competitive retaliation against product	-0.04	0.73	0.03	0.82
Speed of change in technology in the product-market	0.04	0.73	0.17	0.19
Level of support from distributors	-0.14	0.27	0.14	0.26
Level of product's differentiation from competitors	0.03	0.80	-0.05	0.69
Likely price position relative to competition	-0.20	0.11	0.14	0.28
Source of product idea (internal or external)	-0.19	0.14	-0.04	0.73
Product's quality compared to competition	0.35	0.005	0.04	0.76
Level of upper management support for the product	-0.09	0.49	0.07	0.60
Focus group's evaluation of the concept	-0.31	0.01	-0.03	0.82
Colleagues' opinions of the product	0.07	0.61	0.12	0.37

Table 29, cont'd.

Information Item	Correlation with EXPERTISE	p	Correlation with EXPERIENCE	p
Salespeople's opinions of the product	-0.16	0.20	0.00	0.99
Number of other products in development	-0.33	0.01	-0.20	0.12
Time from concept approval to introduction of product	0.05	0.69	0.10	0.45
Whether consumers must change their methods of use	0.03	0.83	0.15	0.25
Number of major competitors	-0.04	0.74	0.13	0.30
Whether product is patentable or can be legally protected	-0.13	0.32	0.08	0.53
Projected market share	-0.00	0.98	0.04	0.76
Likelihood of adverse government regulation	-0.01	0.92	0.24	0.06
Results of quantitative analyses of consumer preference	-0.04	0.78	0.04	0.73
Extent of behavior change needed for product use	0.15	0.24	0.17	0.19

Table 30. Correlations between Number of Items Searched and Experience and Expertise

Correlation between Number of Items Searched and Experience and Expertise

Measure	Good Concept		Bad Concept		Mixed Concept		Total Searched	
	r	p	r	p	r	p	r	p
Expertise	-0.22	0.08	-0.17	0.20	-0.31	0.02	-0.24	0.06
Experience	-0.22	0.09	-0.08	0.56	-0.26	0.04	-0.19	0.14

Table 31. Effects of Interactions between Expertise/Experience and Diagnosticity on Order of Search

Independent Variable	Standardized Parameter Estimates	t	p
Diagnosticity	-0.39	-11.96	0.0001
Expertise	-0.18	-1.64	0.10
Experience	0.03	0.29	0.77
Expertise*Diagnosticity	0.19	1.69	0.09
Experience*Diagnosticity	-0.07	-0.58	0.56

Regression Statistics:
$F_{5,864} = 29.58$, $p = 0.0001$
$R^2 = 0.15$

Table 32. Correlation between Order of Information Search and Diagnosticity by Expertise and Experience

Concept	Correlation between order of search and diagnosticity			
	Low Expertise	p	High expertise	p
Good	-0.39	0.0001	-0.37	0.0001
Bad	-0.26	0.0001	-0.27	0.0001
Mixed	-0.37	0.0001	-0.35	0.0001

Concept	Correlation between order of search and diagnosticity			
	Low Experience	p	High experience	p
Good	-0.36	0.0001	-0.40	0.0001
Bad	-0.24	0.0001	-0.30	0.0001
Mixed	-0.35	0.0001	-0.36	0.0001

Table 33. Results of Logistic Regression of Information Selection on Expertise, Experience and Industry for the Good Concept

Item Description	Number who did not search item	Number who searched item	-2 Log Likelihood X^2	p
Demand made on company's financial resources	13	20	6.89	0.08
Extent of company's experience w/necessary technology	20	12	2.80	0.42
Amount of management's experience w/product and market	21	10	1.42	0.70
Extent of changes needed in distribution system	28	7	9.56	0.02
Ability to use existing sales force	22	4	1.47	0.69
Likely effect on sales of existing product	17	14	2.80	0.42
Whether existing supply channels can be used	28	6	0.71	0.87
Market size	10	21	2.95	0.40
Market growth rate	14	16	11.93	0.008
Whether company can use current production processes	17	6	3.25	0.35
Whether costs drop with volume sold	27	5	0.36	0.95
Level of seasonal/cyclical fluctuations in demand	23	5	4.13	0.25
Market entry costs	9	14	1.32	0.72

Table 33, cont'd.

Item Description	Number who did not search item	Number who searched item	-2 Log Likelihood X^2 [1]	p
Whether competition is vulnerable	10	17	6.82	0.08
Whether product offers a meaningful advantage to users	7	36	3.74	0.29
Strength of existing competitors	9	11	1.14	0.77
Strength of potential competitors not yet in market	17	3	2.85	0.42
Likelihood of new competitive entry into the market	10	6	15.45	0.002
Likelihood of competitive retaliation against product	8	3	7.63	0.05
Speed of change in technology in the product-market	8	10	1.05	0.79
Level of support from distributors	13	4	---	---
Level of product's differentiation from competitors	7	20	2.66	0.45
Likely price position relative to competition	10	10	7.09	0.07
Source of product idea (internal or external)	30	5	3.28	0.35
Product's quality compared to competition	13	14	0.72	0.87
Level of upper management support for the product	15	13	4.06	0.25

[1] Note that --- means the -2 log likelihood estimate did not converge to a solution.

Table 33, cont'd.

Item Description	Number who did not search item	Number who searched item	-2 Log Likelihood X^2	p
Focus group's evaluation of the concept	8	11	1.44	0.70
Colleagues' opinions of the product	6	5	3.05	0.38
Salespeople's opinions of the product	6	4	2.05	0.56
Number of other products in development	10	5	0.94	0.82
Time from concept approval to introduction of product	10	15	4.53	0.21
Whether consumers must change their methods of use	9	12	1.78	0.62
Number of major competitors	11	8	4.11	0.25
Whether product is patentable or can be legally protected	8	8	0.99	0.80
Projected market share	3	11	5.36	0.15
Likelihood of adverse government regulation	20	12	2.69	0.44
Results of quantitative analyses of consumer preference	7	7	1.42	0.70
Extent of behavior change needed for product use	11	10	2.04	0.56

Table 34. Results of Logistic Regression of Information Selection on Expertise, Experience and Industry for the Bad Concept

Item Description	Number who did not search item	Number who searched item	-2 Log Likelihood X^2 [1]	p
Demand made on company's financial resources	20	13	4.95	0.18
Extent of company's experience w/necessary technology	13	19	---	---
Amount of management's experience w/product and market	20	11	2.44	0.49
Extent of changes needed in distribution system	30	5	2.80	0.42
Ability to use existing sales force	22	4	3.52	0.32
Likely effect on sales of existing product	25	6	---	---
Whether existing supply channels can be used	29	5	3.22	0.36
Market size	15	16	6.64	0.08
Market growth rate	18	12	5.30	0.15
Whether company can use current production processes	18	5	1.25	0.74
Whether costs drop with volume sold	27	5	0.25	0.97
Level of seasonal/cyclical fluctuations in demand	24	4	4.60	0.20
Market entry costs	13	10	8.06	0.04

[1] Note that --- means the -2 log likelihood estimate did not converge to a solution.

Table 34, cont'd.

Item Description	Number who did not search item	Number who searched item	-2 Log Likelihood X^2 [1]	p
Whether competition is vulnerable	17	10	3.70	0.30
Whether product offers a meaningful advantage to users	15	28	3.48	0.32
Strength of existing competitors	13	7	1.86	0.60
Strength of potential competitors not yet in market	18	2	1.60	0.66
Likelihood of new competitive entry into the market	12	4	1.46	0.69
Likelihood of competitive retaliation against product	7	4	4.45	0.22
Speed of change in technology in the product-market	13	5	5.58	0.13
Level of support from distributors	14	3	---	---
Level of product's differentiation from competitors	13	14	0.68	0.88
Likely price position relative to competition	14	6	2.19	0.53
Source of product idea (internal or external)	31	4	0.79	0.85
Product's quality compared to competition	14	13	0.60	0.90
Level of upper management support for the product	18	10	1.34	0.72

[1] Note that --- means the -2 log likelihood estimate did not converge to a solution.

Table 34, cont'd.

Item Description	Number who did not search item	Number who searched item	-2 Log Likelihood X^2 [1]	p
Focus group's evaluation of the concept	10	9	5.33	0.15
Colleagues' opinions of the product	8	3	1.39	0.71
Salespeople's opinions of the product	7	3	1.53	0.68
Number of other products in development	10	5	3.94	0.27
Time from concept approval to introduction of product	14	11	0.08	0.99
Whether consumers must change their methods of use	16	5	3.03	0.39
Number of major competitors	12	7	12.37	0.006
Whether product is patentable or can be legally protected	12	4	---	---
Projected market share	8	6	3.28	0.35
Likelihood of adverse government regulation	23	9	6.56	0.09
Results of quantitative analyses of consumer preference	8	6	2.88	0.41
Extent of behavior change needed for product use	10	11	1.45	0.69

[1] Note that --- means the -2 log likelihood estimate did not converge to a solution.

Table 35. Results of Logistic Regression of Information Selection on Expertise, Experience and Industry for the Mixed Concept

Item Description	Number who did not search item	Number who searched item	-2 Log Likelihood X^2	p
Demand made on company's financial resources	15	18	4.23	0.24
Extent of company's experience w/necessary technology	20	12	4.02	0.26
Amount of management's experience w/product and market	25	6	7.11	0.07
Extent of changes needed in distribution system	30	5	1.51	0.68
Ability to use existing sales force	20	6	13.93	0.003
Likely effect on sales of existing product	19	12	0.42	0.94
Whether existing supply channels can be used	28	6	9.81	0.02
Market size	11	20	9.92	0.02
Market growth rate	10	20	3.25	0.35
Whether company can use current production processes	19	4	4.09	0.25
Whether costs drop with volume sold	29	3	0.58	0.90
Level of seasonal/cyclical fluctuations in demand	23	5	5.68	0.13
Market entry costs	10	13	2.81	0.42

Table 35, cont'd.

Item Description	Number who did not search item	Number who searched item	-2 Log Likelihood X^2 [1]	p
Whether competition is vulnerable	11	16	0.91	0.82
Whether product offers a meaningful advantage to users	7	36	1.14	0.77
Strength of existing competitors	10	10	1.67	0.64
Strength of potential competitors not yet in market	16	4	2.62	0.45
Likelihood of new competitive entry into the market	11	5	6.45	0.09
Likelihood of competitive retaliation against product	6	5	---	---
Speed of change in technology in the product-market	13	5	2.79	0.43
Level of support from distributors	15	2	---	---
Level of product's differentiation from competitors	16	11	5.19	0.16
Likely price position relative to competition	12	8	3.30	0.35
Source of product idea (internal or external)	31	4	3.62	0.30
Product's quality compared to competition	11	16	1.85	0.60
Level of upper management support for the product	18	10	1.57	0.67

[1] Note that --- means the -2 log likelihood estimate did not converge to a solution.

Table 35, cont'd.

Item Description	Number who did not search item	Number who searched item	-2 Log Likelihood X^2	p
Focus group's evaluation of the concept	6	13	5.14	0.16
Colleagues' opinions of the product	6	5	4.84	0.18
Salespeople's opinions of the product	6	4	1.64	0.89
Number of other products in development	6	9	5.20	0.16
Time from concept approval to introduction of product	12	13	1.08	0.78
Whether consumers must change their methods of use	10	11	5.40	0.14
Number of major competitors	9	10	12.88	0.005
Whether product is patentable or can be legally protected	12	4	---	---
Projected market share	5	9	4.10	0.25
Likelihood of adverse government regulation	20	12	6.93	0.07
Results of quantitative analyses of consumer preference	8	6	1.93	0.59
Extent of behavior change needed for product use	10	11	1.31	0.73

[1] Note that --- means the -2 log likelihood estimate did not converge to a solution.

Table 36. Time Spent in Information Search

Industry	Time Spent Searching for Information (in seconds)							
	Good Concept		Bad Concept		Mixed Concept		All Concepts	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Pharmaceutical	164.90	217.39	103.59	80.37	122.48	118.13	390.97	312.44
Software	103.61	97.75	64.41	38.18	85.17	41.64	246.96	119.68
All Respondents	138.34	177.26	86.61	67.93	105.97	93.68	327.22	255.15

Results of repeated measures t-tests on amount of time spent in search across concepts

Difference between	Mean difference, (seconds)	Std. Dev.	t	p
Good vs. Bad	51.29	177.28	2.24	0.03
Bad vs. Mixed	-19.29	103.38	-1.45	0.15
Mixed vs. Good	-32.01	165.20	-1.50	0.14

Table 37. Results of T-tests on Mean Search Time by Industry

Concept	Mean Time Spent in Search		t	p	Effect Size, d
	Pharmaceutical Industry	Software Industry			
Good	164.90	103.61	1.46	0.15	0.39
Bad	103.59	64.41	2.50	0.02	0.66
Mixed	122.48	85.17	1.71	0.09	0.45
TOTAL	390.97	246.96	2.47	0.02	0.64

Table 38. Results of Regressing Time Spent in Search on Experience and Expertise

Independent Variable	Parameter Estimate	t	p
Expertise	-0.48	-2.59	0.02
Experience	0.45	2.42	0.02

Model fit statistics:
$F_{2,24} = 4.69$, $p = 0.02$
$R^2 = 0.28$
Adjusted $R^2 = 0.22$

Table 39. Crosstabulations on Use of Cutoffs by Industry[1]

Industry	Use Cutoff on **Market Size**? Yes	No	TOTAL
Pharmaceutical	30 (28.4)	4 (5.6)	34
Software	21 (22.6)	6 (4.4)	27
TOTAL	51	10	61

X^2 with 1 df = 1.20, p = 0.27

Industry	Use Cutoff on **Market Growth Rate**? Yes	No	TOTAL
Pharmaceutical	25 (22.9)	9 (11.1)	34
Software	16 (18.1)	11 (8.9)	27
TOTAL	41	20	61

X^2 with 1 df = 1.39, p = 0.24

[1]Please note that the expected cell frequency is in ( ) below the actual frequency.

Table 39, Cont'd.

Industry	Use Cutoff on **Number of Competitors?**		TOTAL
	Yes	No	
Pharmaceutical	22 (20.6)	12 (13.4)	34
Software	15 (16.4)	12 (10.6)	27
TOTAL	37	24	61

X^2 with 1 df = 0.53, p = 0.47

Industry	Use Cutoff on **Time from Concept Approval to Introduction?**		TOTAL
	Yes	No	
Pharmaceutical	15 (20.1)	19 (13.9)	34
Software	21 (15.9)	6 (11.1)	27
TOTAL	36	25	61

X^2 with 1 df = 7.05, p = 0.008

Table 40. Effects of Expertise and Experience on Use of Cutoffs

Cutoff on	β_1Expertise	β_2Experience	- 2 Log Likelihood (df = 2)	p
Market Size	0.10	0.03	0.33	0.85
Market Growth Rate	0.30	-0.12	3.06	0.22
Number of competitors	0.20	0.01	1.83	0.40

Cutoff on Development Time

Industry	β_1Expertise	β_2Experience	- 2 Log Likelihood (df = 2)	p	Odds Ratio	
					β_1	β_2
Pharmaceutical	-0.42	0.37	4.11	0.13	0.45	2.07
Software	-0.24	0.64	4.72	0.10	0.66	2.86

Table 41. Results of T-tests on Mean Cutoffs by Industry

Cutoff on	Pharmaceutical Industry Mean	Software Industry Mean	t	p	Effect size, d
Market size, $ millions	142.00	16.73	3.33	0.002	0.95
Market growth rate, %	10.52	18.88	-3.36	0.002	1.08
Development time, years	3.90	1.10	3.44	0.004	1.18
Number of competitors	7.05	6.00	0.77	0.451	0.26

Table 42. Results of Regression of Cutoff Values on Expertise and Experience

Dependent Variable: Cutoff on Market Size

Industry	F	p	R^2	Adjusted R^2
Pharmaceutical	4.59	0.02	0.25	0.20
Software	6.22	0.01	0.41	0.34

Parameter Estimates for Above Model

Variable	Standardized Parameter Estimates					
	Pharmaceutical Industry	t	p	Software Industry	t	p
Expertise	0.42	2.38	0.02	-0.06	-0.30	0.770
Experience	-0.45	-2.56	0.02	0.66	3.41	0.003

Table 42, Cont'd.

Dependent Variable: Cutoff on Market Growth Rate

Industry	F	p	R^2	Adjusted R^2
Pharmaceutical	0.52	0.60	0.04	-0.04
Software	1.51	0.26	0.19	0.06

Parameter Estimates for Above Model

Variable	Standardized Parameter Estimates					
	Pharmaceutical Industry	t	p	Software Industry	t	p
Expertise	-0.06	-0.28	0.78	-0.39	-1.40	0.18
Experience	-0.18	-0.80	0.43	0.42	1.52	0.15

Table 42, Cont'd.

Dependent Variable: Cutoff on Development Time

Industry	F	p	R^2	Adjusted R^2
Pharmaceutical	3.03	0.09	0.34	0.23
Software	1.16	0.34	0.12	0.02

Parameter Estimates for Above Model

	Standardized Parameter Estimates					
Variable	Pharmaceu-tical Industry	t	p	Software Industry	t	p
Expertise	-0.62	-2.39	0.03	-0.08	-0.36	0.73
Experience	0.12	0.47	0.65	0.35	1.52	0.15

Table 42, Cont'd.

Dependent Variable: Cutoff on Number of Competitors

Independent Variable	Parameter Estimate	t	p
Expertise	-0.18	-0.95	0.35
Experience	0.01	0.05	0.96

Model Fit Statistics:

$F_{2,33} = 0.50$, $p = 0.61$
$R^2 = 0.03$
Adjusted $R^2 = -0.03$

Table 43. **Crosstabulations of Decision to Send NPC on to Development by Industry**[1]

Industry	**Good Concept** Sent on to Development? Yes	No	TOTAL
Pharmaceutical	31 (31.2)	3 (2.8)	34
Software	24 (23.8)	2 (2.2)	26
TOTAL	55	5	60

X^2 with 1 df = 0.02, p = 0.88
Number missing = 2

Industry	**Bad Concept** Sent on to Development? Yes	No	TOTAL
Pharmaceutical	4 (3.4)	30 (30.6)	34
Software	2 (2.6)	24 (23.4)	26
TOTAL	6	54	60

X^2 with 1 df = 0.27, p = 0.60
Number missing = 2

[1]Please note that the expected cell frequency is in ( ) below the actual frequency.

Table 43, Cont'd.

Industry	**Mixed Concept** Sent on to Development?		TOTAL
	Yes	No	
Pharmaceutical	9 (11.1)	25 (22.9)	34
Software	11 (8.9)	16 (18.1)	27
TOTAL	20	41	61

X^2 with 1 df = 0.27, p = 0.60
Number missing = 1

Table 44. Mean Ratings of New Product Concepts

Concept	All Respondents		Pharmaceutical Industry		Software Industry	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Good	2.43	1.58	2.66	1.54	2.13	1.61
Bad	-2.81	1.67	-2.22	1.67	-3.59	1.34
Mixed	-1.29	2.50	-1.32	2.33	-1.24	2.74

Results of repeated measures t-tests on ratings of new product concepts

Difference between	Mean difference	Std. Dev.	t	p
Good vs. Bad	5.24	2.19	18.58	0.0001
Bad vs. Mixed	-1.49	2.92	-3.94	0.0002
Mixed vs. Good	-3.75	2.99	-9.72	0.0001

Table 44, cont'd.

Concept	Means		t	p	Effect Size, d
	Pharmaceutical Industry	Software Industry			
Good	2.66	2.13	1.23	0.20	0.34
Bad	-2.22	-3.59	3.42	0.001	0.90
Mixed	-1.32	-1.24	-0.11	0.91	0.03

Table 45. Effects of Expertise and Experience on Go/NoGo Decisions

Concept	-2 Log Likelihood Estimate	p	β_1 Expertise	p	Odds Ratio	β_2 Experience	p	Odds Ratio
Good	4.88	0.09	-0.45	0.07	0.429	-0.41	0.53	NS
Bad	4.82	0.09	-0.65	0.08	0.292	0.51	0.23	NS
Mixed	1.36	0.51	0.06	0.69	NS	0.16	0.40	NS

Note: NS = Not Significant

Table 46. Results of Regression of Concept Ratings on Expertise and Experience

Concept	F	p	Standardized Parameter Estimates					
			Expertise	t	p	Experience	t	p
Good	2.66	0.08	0.30	2.21	0.03	-0.02	-0.14	0.89
Mixed	1.16	0.32	-0.19	-1.38	0.17	-0.02	-0.12	0.90

Results for Bad Concept

Industry	F	p	Standardized Parameter Estimates					
			Expertise	t	p	Experience	t	p
Pharmaceutical	0.12	0.89	0.08	0.41	0.68	0.02	0.10	0.92
Software	0.31	0.74	0.06	0.30	0.77	-0.17	-0.78	0.44

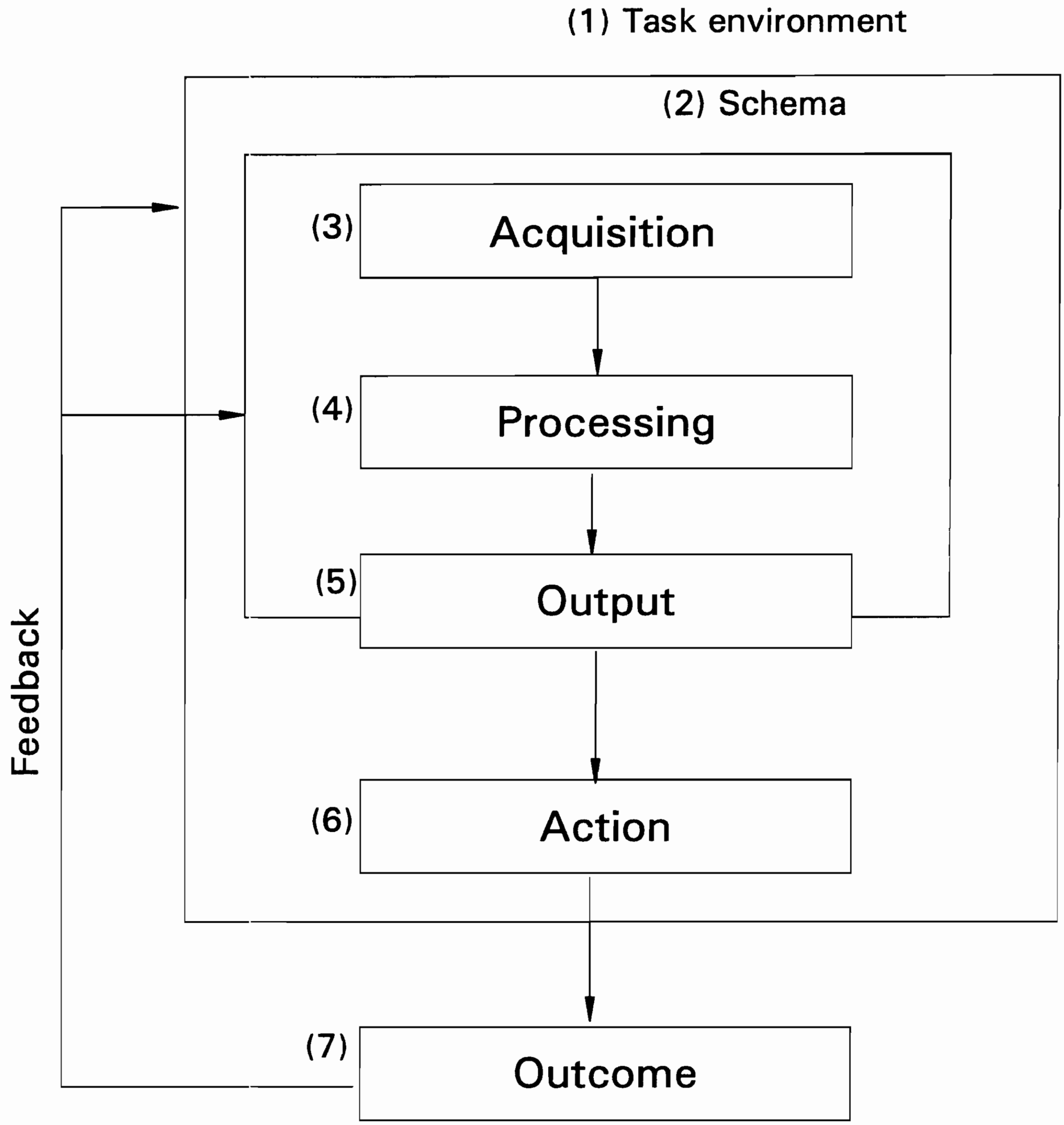

Figure 1. A Conceptual Model of Human Decision Making (Adapted from Hogarth (1989))

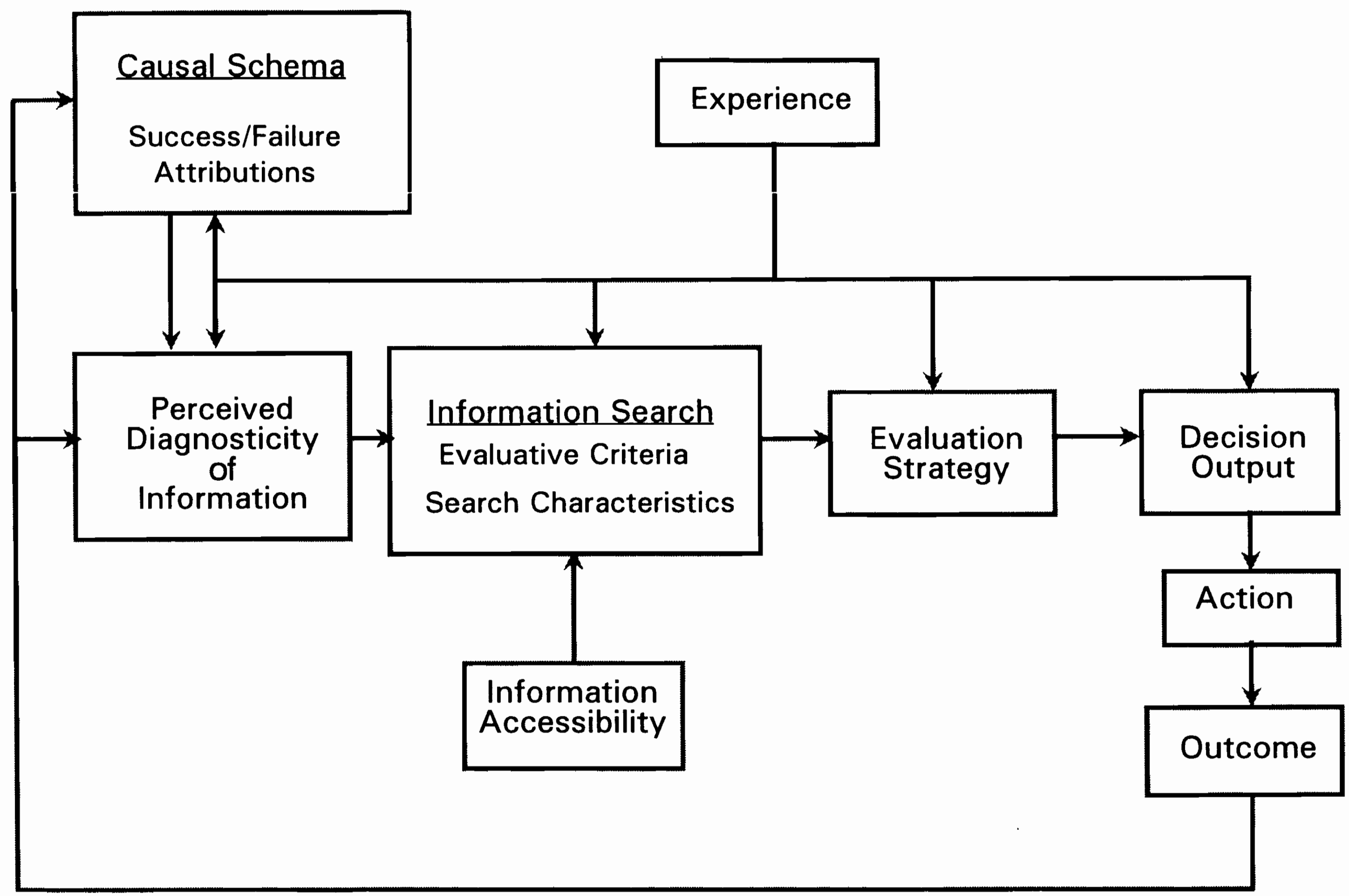

Figure 2. Conceptual Model of New Product Concept Screening

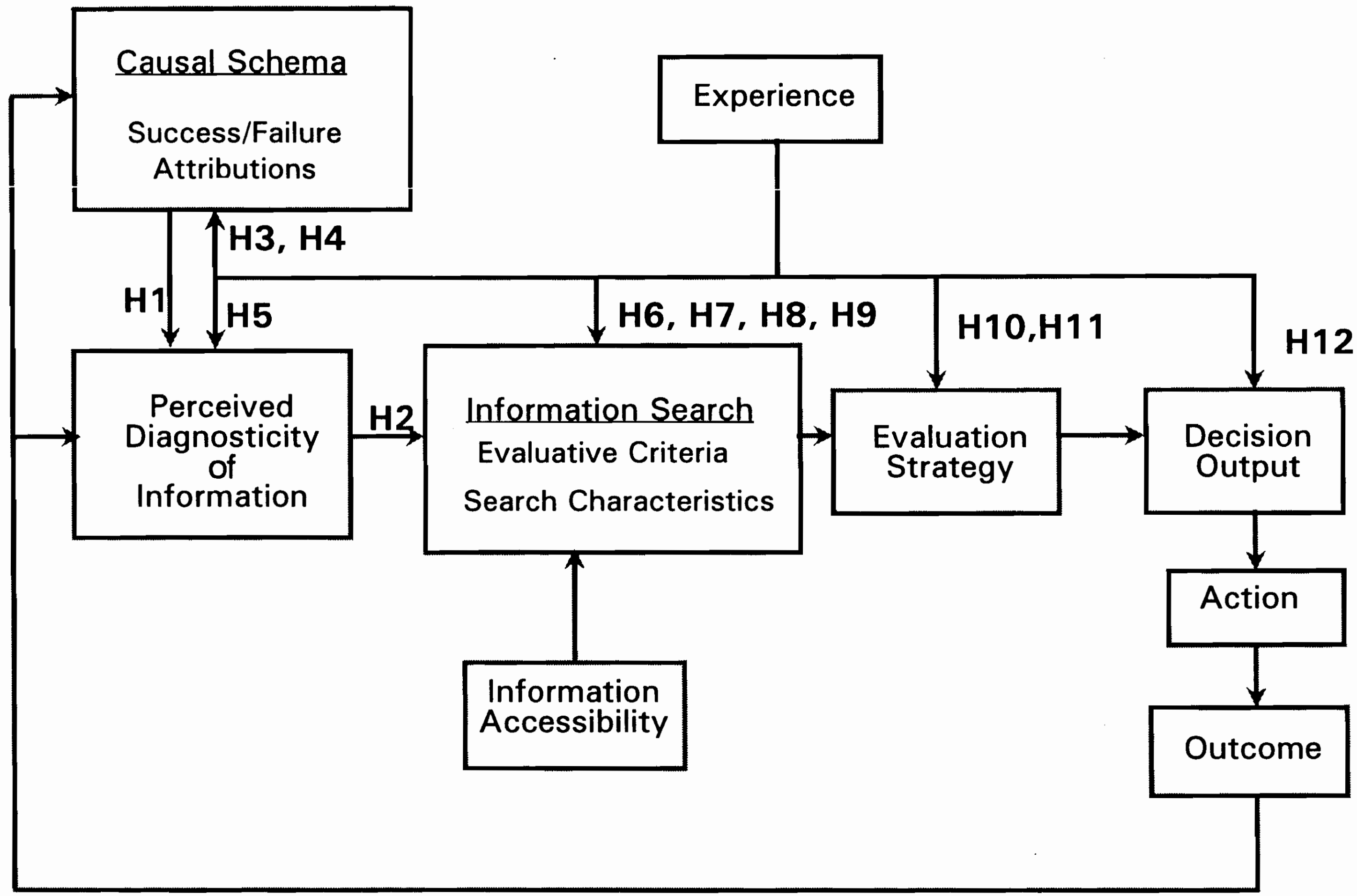

Figure 3. Conceptual Model of New Product Concept Screening Showing Hypotheses

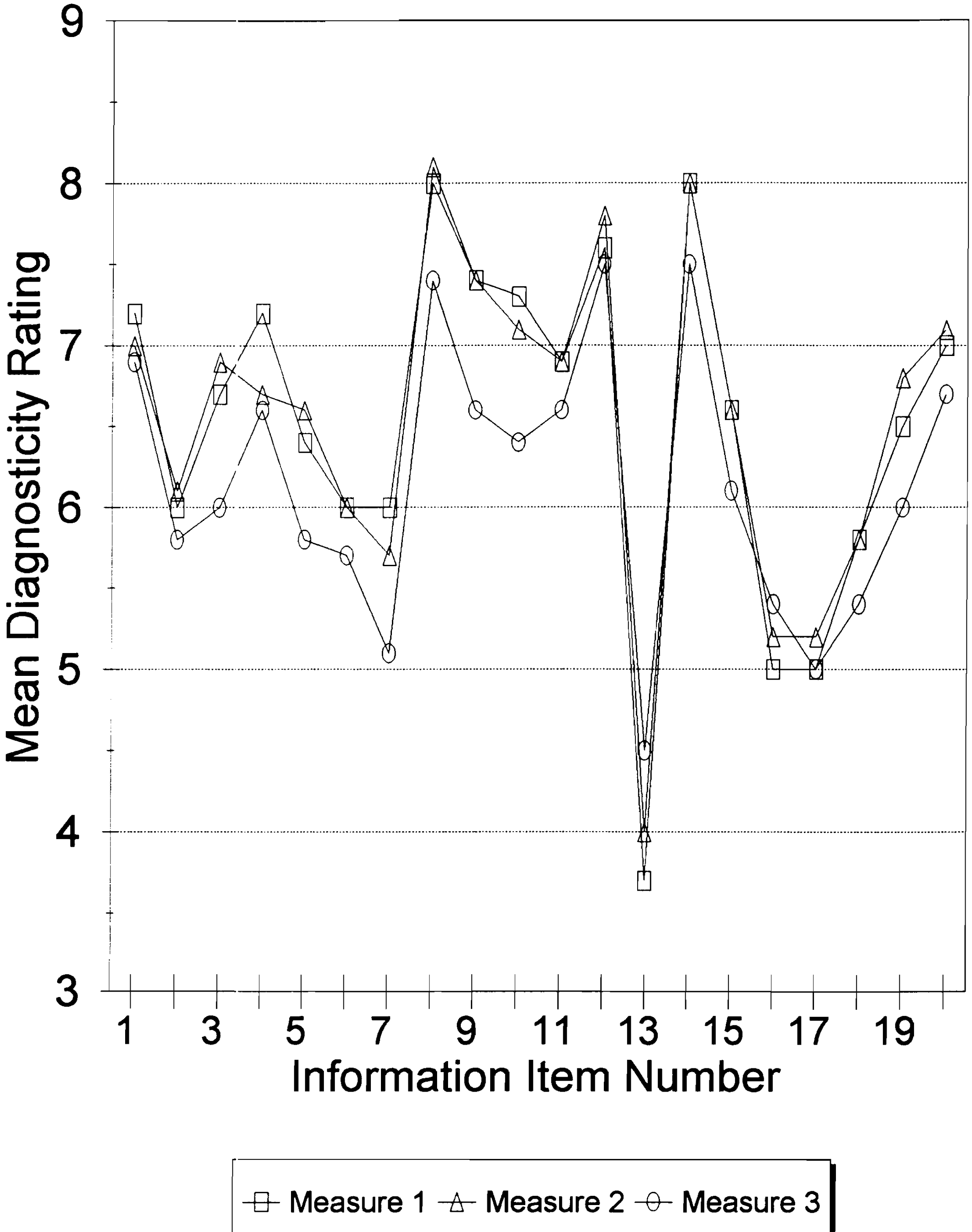

Figure 4. Mean Diagnosticity Ratings
Using 3 measures of diagnosticity

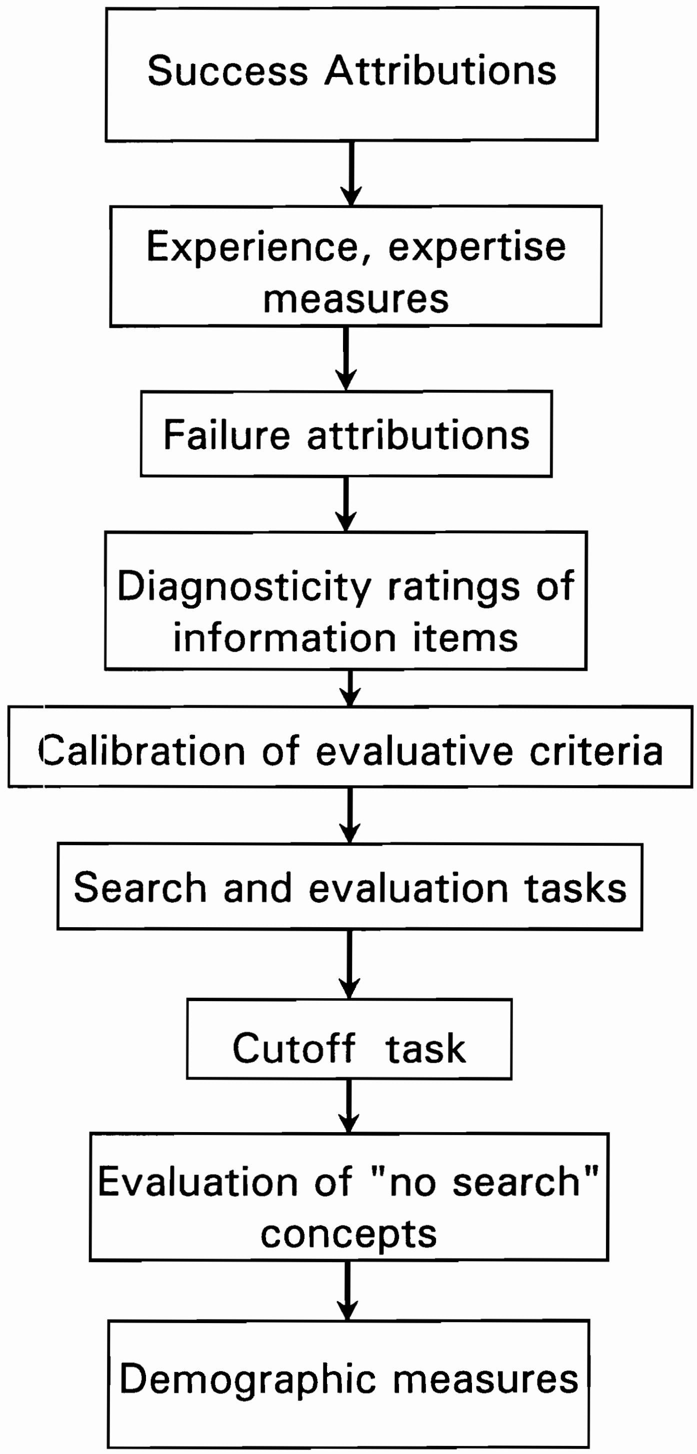

Figure 5. Order of Tasks Performed by Respondents

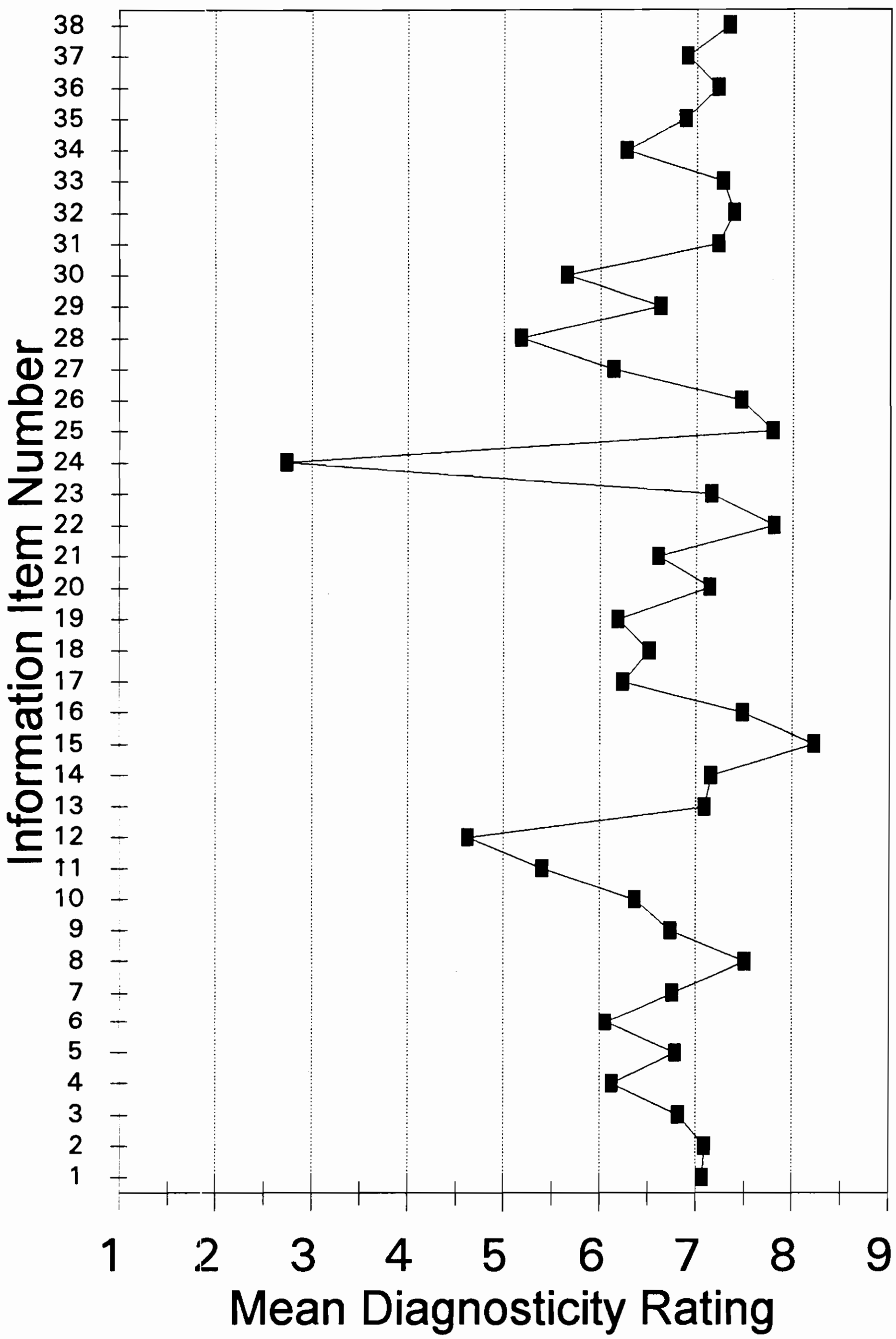

Figure 6. Diagnosticity Ratings

All respondents

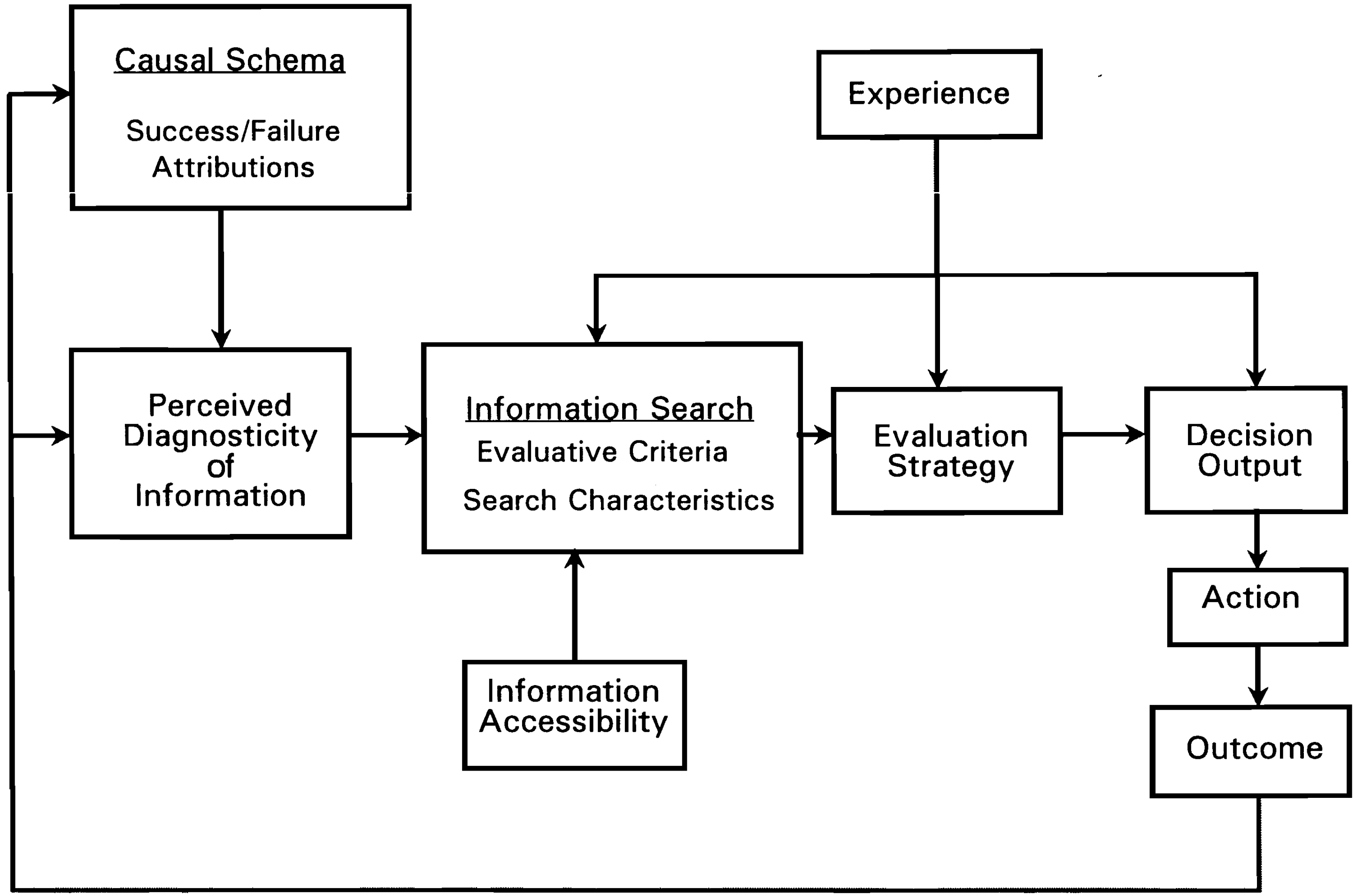

Figure 7. Conceptual Model of New Product Concept Screening Showing Supported Relationships

Appendix

PRINTOUT OF QUESTIONNAIRE FOR PHARMACEUTICALS INDUSTRY

Please note that the formatting of questions on the computer screen might be slightly different than the way it printed out in this Appendix.

checkcol

If this screen appears in color, press C.

If it does not appear in color, press any other key.

Intro1

Welcome to our survey!

We are interested in understanding how new product concepts are evaluated. To do this, we need some information from professionals like you, who are involved in new product development.

We appreciate your help!

Press any key to continue.

----

intro2

When we say new product concepts, we mean ideas for new products which are still in the preliminary stages. New product concepts are usually evaluated very early in the new product development process, before any kind of financial analysis of potential new products takes place.

Press any key to continue.

Intro3

We expect to find a variety of opinions about new product concepts. There are no right or wrong answers, we're just concerned with what you think about new product concepts. Your answers will be kept confidential.

Although it would be best to do this without stopping, we know that you're busy and may be interrupted. If so, you may stop this interview at any time and restart it later. To do so, follow the instructions contained in the letter we sent with this diskette. You will be able to stop the questionnaire and restart it later wherever you left off.

Press any key to continue.

----

success

Before we talk further about new product concepts, we'd like to know about your beliefs about why new products succeed in the marketplace.

What factors do you think make a new product a success? A successful new product is one that meets your company's goals, whatever those goals may be. The factors could relate to characteristics of the product, the market, the company, competition or any other area.

List all of the factors you can think of. When you are finished, press ENTER twice. Press F1 if you need help.

Please make your list as complete as possible; ALL of your ideas are important to us.

Industry

Now we'd like to know a little about you.

In what industry are you currently employed?

1 Over-the-counter pharmaceuticals
2 Computer software
3 Other

Indtenre

How long have you worked in this industry?

years

Position

What is your position or job title? Please type in your answer and press ENTER.

NPDTen

How long have you been involved in new product development?

years

----

pknow1

Compared to others in your field, how much do you think you know about evaluating new product concepts? Enter your response based on the scale below.

1 2 3 4 5 6 7 8 9

One of the LEAST knowledgeable	One of the MOST knowledgeable

----

where

Where did you obtain experience in evaluating new product concepts?

1 A former position
2 Current position
3 Both former and current positions
4 No experience

---

current

In your current position, how would you describe your role in the evaluation of new product concepts?

1 Primary decision-maker
2 Give major input to primary decision-maker(s)
3 Give some input to primary decision-maker(s)
4 None

---

former

In your former position(s), how would you describe your role in the evaluation of new product concepts?

1 Primary decision-maker
2 Gave major input to primary decision-maker(s)
3 Gave some input to primary decision-maker(s)
4 None

---

npddecs

How many new product projects have you had a role in evaluating? (Give a rough estimate if the number is large.)

----

prodtype

Are the types of new products your company develops more likely to be extensions of its existing products or are they products unrelated to current products? Using the arrow keys, move the cursor to the position on the scale that shows your response and press ENTER.

```
|-----|-----|-----|-----|-----|-----|-----|-----|-----|
Extensions of                               Unrelated to
Existing Products                          Current products
```

----

pknow2

How frequently do YOU seek advice from OTHERS when evaluating new product concepts?

1 Almost never seek advice
2 Occasionally seek advice
3 Frequently seek advice
4 Almost always seek advice

----

training

Where did you learn to evaluate new product concepts? Select all that apply. Press 6 when you are finished.

1 Formal education
2 Formal on-the-job training
3 On-the-job experience
4 Reading on your own
5 Other
6 NONE/NO MORE/NEXT QUESTION

NPDproc1

We believe that, in general, the new product development process in most organizations begins with idea generation in which new product concepts are sketched out in rough form. Then they are evaluated using different criteria. After this screening, the concepts which survive then go through more rigorous financial evaluation.

Does your company analyze new product concepts in a manner similar to the description above?

1 Yes
2 No

NPDproc2

We believe that, in general, the new product development process in most organizations begins with idea generation in which new product concepts are sketched out in rough form. Then they are evaluated using different criteria. After this screening, the concepts which survive then go through more rigorous financial evaluation.

How does the evaluation of new product concepts differ in your company from the description above? Type in your response. When you are finished, press ENTER twice. Press F1 if you need help.

----

pknow3

Please rate your degree of expertise in evaluating new product concepts compared to others in your field. Enter your response based on the scale below.

1 2 3 4 5 6 7 8 9

One of the LEAST expert	One of the MOST expert

---

group

In your company, does the responsibility for evaluating new product concepts rest with one group or does it change from project to project?

1 Responsibility rests with one group
2 Changes from project to project

Failure

Earlier, we asked you why new products succeed. Now we'd like to know about your beliefs about why new products fail.

What factors do you think make a new product fail? A failure is a product that does not meet your company's goals, whatever those goals may be. The factors could relate to characteristics of the product, the market, the company, competition or any other area.

List all of the factors you can think of. When you are finished, press ENTER twice. Press F1 if you need help.

Please make your list as complete as possible; ALL of your ideas are important to us.

Diagint

Now imagine that you are considering product concepts for a new over-the-counter drug. We will describe pieces of information that could be acquired about this potential new product. Please indicate for each item how useful that piece of information would be in predicting whether the product will succeed or fail. At any time, you may use the Escape key (ESC) to back up and review your answers.

We realize that there are many items. Evaluating new products in your industry can be very complex! We really appreciate your input.

Press any key to continue.

Diag1

HOW USEFUL WOULD THE FOLLOWING PIECE OF INFORMATION ABOUT THE PRODUCT CONCEPT BE IN PREDICTING WHETHER THE PRODUCT WILL SUCCEED OR FAIL IN THE MARKETPLACE?

For the item below, use either the numbers at the top of your keyboard or the ones on the number pad to the right to show your response based on the scale below.

MARKET SIZE

(NOTE: Each of the 38 information items would be rated.)

1 2 3 4 5 6 7 8 9

Not at all useful in predicting success or failure	Extremely useful in predicting success or failure

---

calib

Now we'd like to see how you evaluate some characteristics of products and markets.

Press any key to continue.

Higrow

What annual growth rate, in percent change in sales volume, must a potential market experience for you to consider it to be a high growth market?

%

ENTER 0 IF YOU HAVE NO OPINION ABOUT THIS ITEM.

Lrgmkt

How big does a potential market have to be for you to consider it a large market? (If less than $1 million, use a decimal value.)

$ Million

ENTER 0 IF YOU HAVE NO OPINION ABOUT THIS ITEM.

Entcost

How high do entry costs have to be for you to consider them high? (Entry costs may include all costs associated with development, R&D, market research, initial marketing, etc.) (If less than $1 million, use a decimal value.)

$ Million

ENTER 0 IF YOU HAVE NO OPINION ABOUT THIS ITEM.

Introtim

What is the average time between new product concept evaluation and product introduction for products taken to market?

year(s)

ENTER 0 IF YOU HAVE NO OPINION ABOUT THIS ITEM.

----

compete

On average, how many strong competitors would one of your typical products face in the over-the-counter pharmaceuticals market?

ENTER 0 IF YOU HAVE NO OPINION ABOUT THIS ITEM.

----

hishare

How high would your anticipated market share in an established

OTC drug market have to be for you to consider it high?

%

ENTER 0 IF YOU HAVE NO OPINION ABOUT THIS ITEM.

----

concepts

On average, how many products are in development at the same time in your company?

ENTER 0 IF YOU HAVE NO OPINION ABOUT THIS ITEM.

----

fincrit

Of the following, which are the three most important financial objectives that your company regularly uses in evaluating new product concepts?

Type the number corresponding to the three most important. If your company DOES NOT use any of these criteria, type 9 and press ENTER.

1 Market Share
2 Total Sales
3 Gross Margin
4 Return on Investment (ROI)

5 Net Present Value (NPV)
6 Internal Rate of Return (IRR)
7 Profit
8 Payback Period
9 NONE/NO MORE/NEXT QUESTION

Evintro1

Imagine that your company has been considering three new product concepts. These concepts are currently in the concept testing stage, but the time has now come to decide if each of these concepts should be advanced to the next stage of the new product development process.

Press any key to continue.

Evintro2

Please review each concept and decide whether it would be most appropriate to send it on to the next stage of development or if the concept should be abandoned at this point. You do not need to move forward any particular number of concepts. You may abandon them all or send them all forward in development.

You will see one product concept at a time and make a decision about it. For each concept you evaluate, some information is available. You may use any or all of it. To see a particular piece of information, simply type in its corresponding letterJust a moment, please..another piece of information if you wish. When you decide whether to abandon or move this concept forward, press Z.

Please remember obtaining information is costly in time and money. Please look only at information you feel you need to make the decision.

Press any key to continue.

Srch1-1

Type in the letter corresponding to the item of information you would like to see. WHEN YOU HAVE OBTAINED ENOUGH INFORMATION TO

MAKE YOUR DECISION, PRESS Z.

CONCEPT

A Demand made on company's financial resources
B Extent of company's experience w/necessary technology
C Amount of management's experience w/product and market
D Extent of changes needed in distribution system
E Ability to use existing sales force
F Likely effect on sales of existing products
G Whether existing supply channels can be used
H Market size
I Market growth rate, (% change in $ volume)
J Whether company can use current production processes
K Whether costs drop with volume sold
L Level of seasonal/cyclical fluctuations in demand
M Market entry costs
N Whether competition is vulnerable
O Whether product offers a meaningful advantage to users
Z READY TO EVALUATE PRODUCT

(NOTE: The actual items which appeared depended on the respondent's diagnosticity ratings of the 38 information items.)

---

ready1

Press any key to make your evaluation

---

go/nogo1

Should this concept be sent on to the next stage of development?

1 YES
2 NO

Eval1

How likely do you think it is that this new product concept will be a success or a failure? Move the cursor to the position on the scale that shows your response.

Just a moment, please..

|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|

Very Likely to Fail	Equally Likely to Succeed or Fail	Very Likely to Succeed

---

(NOTE: Concepts 2 and 3 were presented in the same way as question Srch1-1 above.)

cutoff1

Now, imagine that you are evaluating new product concepts for established OTC pharmaceuticals markets. You have a staff who might aid you in the evaluation of these concepts. You have the option of evaluating all available new product concepts yourself or you can request that your staff screen the concepts using various criteria so that you need not bother evaluating concepts that have some very negative characteristic.

Press any key to continue.

---

cutoff2

Suppose that your staff can screen these concepts on any of four different criteria:

First, tell us for each criterion whether you would want your staff to screen on it. If you do, we will then ask you how good a concept will have to be on that criterion to be passed on to you.

Press any key to continue.

---

cutmktsz

Would you like to have your staff screen out any product concepts on the basis of market size?

1 Yes

2 No

---

mktsize

How large would a market have to be to make it worth your while to look at the concept, rather than having your staff screen it out?

$ Million

----

ctgrowth

Would you like to have your staff screen out any product concepts on the basis of market growth rate?

1 Yes
2 No

----

grwthcut

How large would a market's growth rate have to be to make it worth your while to look at the concept, rather than having your staff screen it out?

%

----

ctintro

Would you like to have your staff screen out any product concepts on the basis of estimated time from concept approval to product introduction?

1 Yes
2 No

---

introct1

How short would a product concept's estimated time from approval to product introduction have to be to make it worth your while to look at the concept, rather than having your staff screen it out? (You may use one decimal place, as in .5 years.)

years

---

ctcomp

Would you like to have your staff screen out any product concepts on the basis of the number of major competitors?

1 Yes
2 No

---

compcut

How many major competitors would be so many that it wouldn't be worth your while to look at the concept?

----

introno1

Now we would like you to look at descriptions of new product concepts for an established OTC pharmaceuticals market and tell us what you think of them. This time, you will not have to search for information; several items of information about the product concept will be displayed. However, this information will be limited. Make your evaluation assuming that the product is acceptable on all other dimensions.

Press any key to continue.

----

nosrch1

Size of the market for the product	$ 200 MILLION
Cost of entry into the market	$ 5 MILLION
Product quality relative to competitive products	COMPARABLE
Upper management support for the product	LOW
Management's experience with product-market	NONE

(NOTE: For the above and the next questions, values for market size and entry cost depended on respondent's answers to 'calibration' questions.)

Should this concept be sent on to the next stage of development?

1 Yes
2 No

----

nseval1

How likely do you think it is that this new product concept will be a success or a failure? Move the cursor to the position on the scale that shows your response.

```
|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
Very                 Equally              Very
Likely              Likely to             Likely
to Fail           Succeed or Fail        to Succeed
```

---

nosrch2

Size of the market for the product $ 500 MILLION

Cost of entry into the market $ 10 MILLION

Product quality relative to competitive products COMPARABLE

Upper management support for the product HIGH

Management's experience with product-market EXTENSIVE

Should this concept be sent on to the next stage of development?

1 Yes
2 No

----

nseval2

How likely do you think it is that this new product concept will be a success or a failure? Move the cursor to the position on the scale that shows your response.

```
|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
Very                    Equally                     Very
```

Likely to Fail	Likely to Succeed or Fail	Likely to Succeed

---

nosrch3

Size of the market for the product	$ MILLION
Cost of entry into the market	$ MILLION
Product quality relative to competitive products	COMPARABLE
Upper management support for the product	HIGH
Management's experience with product-market	EXTENSIVE

Should this concept be sent on to the next stage of development?

1 Yes
2 No

(NOTE: For the above question, values for market size depended on respondent's cutoff. Value for entry cost depended on respondent's answers to 'calibration' questions.)

nseval3

How likely do you think it is that this new product concept will be a success or a failure? Move the cursor to the position on the scale that shows your response.

```
|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
Very                Equally               Very
Likely             Likely to             Likely
to Fail          Succeed or Fail        to Succeed
```

----

educlvl

Now we'd like to ask you some questions about yourself, so that we can group your responses with those of similar people.

What is the highest level of education you have attained? Enter the number corresponding to your answer.

1 Attended high school, but did not finish
2 Finished high school
3 Some college
4 College graduate
5 Some postgraduate coursework
6 Master's degree
7 Ph.D.
8 Other

Educback

In what field was your highest degree obtained? Choose one from the following list. If you have more than one degree, choose the number for the last degree you obtained.

1 Business
2 Computer Science
3 Engineering
4 Humanities/Liberal Arts
5 Medicine
6 Mathematics
7 Physical Sciences
8 Social Sciences
9 Other

Funcback

What is the functional area of your current position?

1 Accounting
2 Engineering
3 Finance
4 Marketing
5 Production/Operations Management
6 Research and Development
7 Other

----

gender

Are you male or female?

1 Male
2 Female

---

age

What is your age? Please enter the number which corresponds to the appropriate age category.

1 Under 22

2 22 - 30
3 31 - 40
4 41 - 50
5 51 - 60
6 61 - 65
7 66 and over

Percept1

We greatly appreciate your answering the previous questions.

Now, we'd like your opinion on the questions you have just answered and on this study in general. Please give us your honest opinion.

Press any key to continue.

Inforeal

Were the questions and information presented meaningful?

```
|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
Not at all                                           Very
Meaningful                                     Meaningful
```

----

notmean

Please describe briefly why some parts of the questionnaire were not meaningful. When you are finished, press ENTER twice. Press F1 if you need help.

----

info

Is there any other information you would routinely have or try to discover about a new product concept that was not discussed here?

1 Yes
2 No

----

otherinf

Please describe briefly what other information you would routinely have or try to discover about a new product concept that was not discussed here.

When you are finished, press ENTER twice. Press F1 if you need help.

----

goodbye

Thank you very much for your participation!
We hope to learn a lot from professionals like yourself.

Press any key to end the questionnaire. When the screen goes blank, please remove the diskette, put it in the prepaid diskette mailer and return it to us.

We will share results of this survey with all companies that participate.

Good-bye!

PRESS ANY KEY TO END THE QUESTIONNAIRE.

VITA

MICHELLE R. HUNT

Michelle R. Hunt

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EDUCATION

Doctor of Philosophy in Marketing	Virginia Polytechnic Institute & State University Completed: Summer,1994 Overall GPA: 3.7/4.0
Bachelor of Science in Mechanical Engineering	Massachusetts Institute of Technology June, 1982 Overall GPA: 4.1/5.0

REFERRED CONFERENCE PROCEEDINGS

Hunt, Michelle R. (1991), "Top Management Agreement on Marketing Strategy and Environmental Uncertainty: Implications for Theory and Practice," in Mary C. Gilly et. al. (eds.), *1991 AMA Educators' Proceedings*, p. 78-88, Chicago: American Marketing Association.

WORKING PAPERS

Lee, Renee G., Julia M. Bristor, and Michelle R. Hunt, "The Image of Blacks in Advertising," (submitted to a special issue of the *Journal of Public Policy and Marketing*)

Hunt, Michelle R. and Noreen M. Klein, "An Application of Three Strategic Typologies to Marketing" (to be submitted to *Journal of Marketing*)

Hunt, Michelle R., "The Impact of Feedback on Salespeople's Performance: A Reanalysis of Jaworski and Kohli (1991) Using LISREL" (to be submitted to *Journal of Marketing Research*)

AWARDS AND HONORS

Hunt, Michelle R. (1993), "The Screening of New Product Concepts: Information Use and the Effects of Managerial Experience," awarded first place in the 1993 Product Development and Management Association Dissertation Proposal Competition.

Awarded Virginia Tech's Presidential Fellowship for the College of Business 1988-91.

Awarded the Commonwealth Fellowship by the State Council of Higher Education for Virginia 1992-93.

Chosen to participate in the Advertising Educational Foundation's Visiting Professor Program, Summer 1994.

PROFESSIONAL PRESENTATIONS

"Experience Effects in New Product Concept Screening," presented at the Product Development and Management Association Conference, October 22, 1993, San Diego, CA.

TEACHING EXPERIENCE

University of North Carolina:

BA 160	Principles of Marketing
BA 161	Advertising Management

Virginia Tech:

Mktg 3104	Principles of Marketing
Mktg 4254	Product and Price Management

MEMBERSHIP IN PROFESSIONAL ASSOCIATIONS

American Marketing Association
Academy of Marketing Science
Product Development and Management Association

REVIEWING ACTIVITIES

Ad Hoc Reviewer for American Marketing Association *Proceedings of the 1994 Winter Educators' Conference*

WORK EXPERIENCE

Hayes, Seay, Mattern & Mattern   Roanoke, VA   October, 1985 - August, 1988

Assistant to the Marketing Vice-President--Aided Marketing VP with market research and with preparation of reports presented to Board of Directors.

Mechanical Engineer--Designed heating, ventilating and air conditioning systems for industrial and educational buildings.

Structural Engineer--Designed and analyzed structures for buildings and flood control projects. Also developed BASIC structural analysis programs used by the Structures Department.

Production Assistant--Aided production manager in calculating and forecasting company workload. Also aided in financial tracking of key firm projects.

United Technologies Research Center, Optics Group West Palm Beach, FL 1984-1985

Mechanical Engineer--Designed and analyzed components for high energy laser applications.

Pennysaver, a division of the Palm Beach Post West Palm Beach, FL 1983-1984

Advertising Sales--Sold advertising for a local newspaper insert. Involved in canvassing for new accounts and servicing existing accounts. Also aided in ad layout and design.