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DETERMINANTS OF PROBLEM REDEFINITION: AN INFORMATION PROCESSING APPROACH

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ABSTRACT

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Cybernetic theory suggests that decision makers monitor environmental variables in order to determine when the definition of their current problem has undergone a change. Previous decision making research, however, has neglected to identify the determinants decision makers use in compiling the environmental information before making a change in the definition of the problem. This study investigated the hypothesis that various information processing variables, previously identified in other theoretical areas, had a significant relationship with decision makers' information compilation strategies. Specifically, it was proposed that these information processing variables interacted with the information on environmental variables to influence decision makers' decision to redefine a given problem situation. Results did not support this hypothesis. Implications for future research are discussed.

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For my family who always stood by me, for the two men who always believed in me, Manish and Mike, and for three true friends, Chris, Don and Dave. Thank you.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

INTRODUCTION

Previous theoretical and empirical literature in decision making has focused mainly on the decision making processes used to solve well-defined problems (Abelson and Levi, 1985). Most models of the decision making process implicitly accept the fact that the decision making process for a well-defined decision consists of four fundamental steps: problem definition, search for alternative solutions, evaluation of alternative solutions, and choice of decision solutions (Abelson and Levi, 1985; Anderson, 1984; Bass, 1981; Pfeffer, 1980; Kilmann and Mitroff, 1979; Janis and Mann, 1977).

Most theoretical and empirical research studies of decision making have investigated optimal methods for solving already well-defined problems. However, as Mintzberg, Raisinghani and Theoret (1976) note, most decisions made in an organizational setting are not well-defined. Top level managers most often have to face ill-structured and complex problems (Walsh, 1987; Bass, 1981; Ungson, Braunstein, and Hall, 1981). The ambiguity present in the problem definition stage is a central characteristic of one of the most important types of decisions managers have to make: strategic decisions (Duhaime and Schwenk, 1985; Schwenk, 1984). Mason and

Mitroff (1981) contend that strategic problems have no clear formulation because they involve complexity, uncertainty and ambiguity. Therefore, it is difficult for managers to satisfactorily define the problem.

According to Lyles and Mitroff (1980), problem definition is an important aspect of the strategic problem solving process because of the ill-defined nature of managerial problems. In their study of organizational problem types, 90% of the problems reported by their sample fell in the ill-defined category. Lyles and Mitroff (1980) conclude that upper management is rarely involved in solving well-defined problems. Indeed, several researchers argue that problem definition is itself an ill-defined, complex and ambiguous problem (Mason and Mitroff, 1981; Kilmann and Mitroff, 1979).

Ill-defined problems are those which may be conceptualized in multiple ways (Lyles, 1981). Ill-defined problems are characterized by ambiguity and incompleteness of information (Bass, 1981; Mason and Mitroff, 1981). For this reason, problem definition is initially unclear and must be refined as the decision maker progresses through the decision process (Thomas, 1984; Mintzberg, et al, 1976). For problems that are ill-defined, problem identification is critical (Lyles and Mitroff, 1980). Due to the ambiguous nature of problem definition, specifications of desired decision outcomes are not readily available to the decision maker (Thomas, 1984). In addition, since these decisions typically extend over time, there are environmental effects on the decisions that decision makers often do not have control over (Johnson, 1988; Walsh, 1987). Problem definition is, therefore, a decision making issue of considerable practical significance (Howard, 1984; Lyles, 1981; Mintzberg, et al, 1976). If decision problems are often initially ill-defined, it is important to ask how decision makers develop their initial and subsequent definitions of the problem. Literature from cognitive psychology provides one possible answer to this question.

Implicit Theories

Some previous work in decision making has integrated cognitive psychology with decision making theory in an effort to understand the stages in the human decision making process. Specifically, this work has speculated that decision makers have implicit theories about the way the world operates (Neisser, 1976; Kelly, 1967; Weick, 1979).

According to the implicit theory thesis, these implicit theories have developed over the course of the decision makers' life experiences and have been formed by societal expectations (Schwenk, 1988; Markus and Zajonc, 1985; Nisbett and Wilson, 1979). People draw on these implicit theories to define the situation as a specific type of problem (Walsh, 1987; Cowan, 1986; Chittipeddi and Gioia, 1983; Taylor and Crocker, 1983; Gilovich, 1981; Newell and Simon, 1972). The implicit theories are particularly salient when the decision maker is faced with ambiguous information (Higgins and Bargh, 1988). On the basis of the belief structures embedded in their implicit theories, people impose a definition on the problem and, thus, frame the decision issues at hand (Shrivastava and Mitroff, 1984; Dutton, Fahey and Narayanan, 1983; Lyles, 1981). This imposed definition includes assumptions about the situation as well as information processing rules that enable the decision maker to encode relevant environmental information and screen out irrelevant information (Cowan, 1986; Stephans, 1985). The definition is not based on the situation or problem at hand, per se, but is more related to the decision makers' past experiences with similar situations (Gilovich, 1981; Nisbett and Wilson, 1977). Once the mind has imposed the definition on the situation, the situation is clear enough to the decision maker that he or she can then attempt to solve it.

The importance of these implicit theories in the decision making process has been especially noted by researchers studying strategic decision making processes (Johnson, 1988; Schwenk, 1988; Smircich and Stubart, 1985;

Daft and Weick, 1984; Hambrick and Mason, 1984). An empirical example of the preceding theoretical framework is provided by Johnson (1988) who conducted a longitudinal case analysis of a British retail company. He found that when the performance of the company fell and the environment indicated the need for a change in company direction, the managers of the retail company defined what changes needed to be made by drawing on their prior experiences in and assumptions about the organization and the market. These prior experiences and assumptions served to guide the company managers in addressing the new problems and in taking future action.

Problem Redefinition

This recent integration of the cognitive aspect of decision making has generated considerable interest in the decision making literature. There has been an increase in the adaptation of principles from cognitive psychology to the problem definition stage of the decision making process (Cowan, 1986; Cowan, 1985; Howard, 1984; Schwenk, 1984; Volkema, 1983; Lyles, 1981; Lyles and Mitroff, 1980). The logical progression from studying issues related to problem definition is a focus on the issues concerning how people redefine the problem when the underlying decision situation has changed.

The decision making process is often dynamic and occurs over time (Volkema, 1983; Mintzberg, et al, 1976). The incorporation of a dynamic research approach to decision making highlights the changing nature of the decision situation that results from repeated interactions with a changing environment (Walsh, 1987; Hogarth, 1981). When the decision situation changes, the definition of the problem often changes (Walsh, 1987). This sequence of events means that the decision maker must change his/her current definition of the problem to a new definition that is more congruent with the new situation. Problem redefinition is a particularily important step when the situation is ill-defined and, therfore, more prone to change (Abelson and Levi, 1985).

The relationship between the changing nature of the environment and the changes in the decision situation is evident in research done by Tushman and his associates (Tushman, 1986; Tushman and Anderson, 1985; Virany, Tushman and Rommanelli, 1985) who focused on organizational decisions over time. They found that the decision situations that the organizations faced changed over time due to environmental factors such as technological changes. Johnson (1988), in a longitudinal analysis of several British retailers, found similar support for the hypothesis that environmental changes lead to organizational decision changes. Lyles (1981) presented a synthesis of her research results in the form of numerous decision cycles that organizations go through. Cycle 5, the most common problem formulation pattern, refers to a decision situation where a definition of a problem is reexamined and often redefined due to a triggering event in the organization or its environment (Lyles, 1981). Walsh (1987) notes that changes that occur in the environment over time often invalidate credible problem formulations. Subsequently, these have to be abandoned for formulations that "fit" with the new problem generated by the changed environment. The incorporation of the idea that the decision situation is dynamic raises the issue of the importance of problem redefinition in the decision making process.

This dynamic quality of the decision situation is not well documented in the traditional decision making research that uses static research designs. Very little work has been focused on studying problem redefinition in decision making. The reason for the lack of interest in problem redefinition may, in large part, be due to the limitations of the research designs used in traditional decision making investigations.

In the past, decision making has been studied by static research designs that look at one decision at one point in time. Few studies have examined decision processes both in context and over time in order to identify how the processes come about (Einhorn and Hogarth, 1982; Johnson, 1988). Furthermore, the problem definition stage has been taken, in general, as a given in these studies (Abelson and Levi, 1985). This is true because much of the focus of the decision making literature has been on well-defined problems where the definition of the problem is clear and unambiguous (Einhorn and Hogarth, 1982). As Abelson and Levi (1985) point out, the research design utilized in these studies and the practice of assuming away the role of problem definition is likely to be ecologically invalid for a broad variety of decisions. Often, researchers assumed that the subjects knew what the decision problem was (Kilmann and Mitroff, 1979). Ebbesen and Konecni (1980) argue that the majority of important decision making studies have been conducted with procedures in which the decision task was broken into parts that were of primary interest to the researcher. Since most of the decision making research has been conducted in a laboratory setting, the research frequently defines the problem for the subject (Kilmann and Mitroff, 1979). In addition, subjects in the traditional decision making research usually were not given a holistic representation of the predecision situation. Rather, they were mostly given lists of the levels of the relevant factors and then told to make a decision (Ebbesen and Konecni, 1980). Ebbesen and Konecni (1980) make a strong argument that the simulated nature of the decision tasks in these studies rarely leads to results that are generalizable to the real world. This criticism of traditional decision making research has been echoed by a number of other prominent researchers (MacCrimmon, 1982; Taylor, 1982; Tversky, 1982). Estes (1980) points out that most applications of behavioral decision theory have been limited to situations where all potential alternatives for the situation are presented to the subject and the subject's task is merely to select from among these. In general, this research has typically focused on the end product of the decision process such as choice rankings (Payne, Braunstein and Carroll, 1978). Finally, most of this research required the subject to make one decision or to work on a single problem. O'Reilly (1983) notes that most decision makers in the lab are focused on a limited information base, a single goal and have no vested interest in the outcomes of the decisions. The environment in the experimental setting also does not contain as much redundancy and complexity as the real world has (MacCrimmon, 1982). As long as decisions are studied as a one shot phenomenon, the issue of problem redefinition does not ever arise.

The Current Study

The question that this study seeks to answer is what causes decision makers to decide that the situation has changed to the extent that they feel it necessary to impose a new definition on the situation? Are decision makers able to identify the change that occurs in the underlying decision situation? In addition, are decision makers able to respond to this change by redefining the situation? New situations present new problems and make other problems obsolete. Decision makers frequently respond to new situations by changing the way they view problems. The fundamental question raised by the issue of problem redefinition is what determinants of a situation lead the individual decision maker to undertake problem redefinition.

Although there has been some case study work done on problem redefinition at an organizational level (e.g., Johnson, 1988; Tushman and Anderson, 1987; Tushman, 1986), little quantitative work has been done on individual problem redefinition. A major reason for this is the static nature of most decision making research to date (Abelson and Levi, 1985).

A discussion of theoretically relevant determinants of problem redefinition and a model of these determinants follows in Chapter One. A set of hypotheses arising from the theoretical discussion will be presented at the conclusion of the chapter. In Chapter Two, the first part of the discussion will center on the application of the problem reformulation model proposed in Chapter One. The second section will present the research design. The results of the research investigation will be presented in Chapter Three. A discussion of the implications of the current line of research and future research avenues will be the subject of Chapter Four.

CHAPTER ONE

THEORETICAL FRAMEWORK FOR A MODEL OF PROBLEM REDEFINITION

As was stated in the Introduction, the problem redefinition stage of individual decision making has not received wide attention in current decision making literature. Aside from the methodological constraints of previous empirical investigations of decision making which led to the neglect of problem redefinition issues, prior theoretical models of decision making also do not incorporate variables related to problem redefinition. Nor does the decision making literature provide a theoretical base for identifying what variables influence decision makers to make a problem redefinition decision. However, some of this theoretical framework may be found in literature outside the mainstream decision making literature.

What follows is a brief review of the major theoretical decision making models and how each model approaches the problem redefinition issues. This will be followed by a more extensive review of literature from a number of research areas which have investigated various issues relating to decision makers' processing and compiling of information. Research from these areas provides theoretical principles that suggest which variables may be determinants of how decision makers compile information to make a problem redefinition decision. The specific hypotheses of this study are presented at the conclusion of the literature review.

Decision Making Models and Problem Redefinition

The review of the literature on decision making model will briefly highlight the broad framework of the rational, satisficing, incremental and cybernetic models of decision making. It will also summarize how each model addresses issues related to the problem redefinition stage.

The Rational Model

The rational model of decision making suggests that decision makers make optimal decision choices after an exhaustive analysis of the identified alternatives (House and Singh, 1987; Janis and Mann, 1977; Lindbloom, 1959; Allison, 1969). In the rational model of decision making, it is assumed that people are unboundedly rational in their decision making and are faced with few time constraints (House and Singh, 1987; Lindbloom, 1979; March and Simon, 1968). The possibility that problem definition may be ambiguous and uncertain is not even raised by the rational model. A strict theoretical interpretation of the rational model suggests that the issue of problem redefinition will never arise for the decision maker because the rational model views the problem definition stage as unproblematic. Indeed, this stage is taken as a given by the model.

The Satisficing Model

The satisficing model does acknowledge cognitive bounds on human decision making (Simon, 1945). On the basis of this assumption, the satisficing model suggests that decision makers are motivated to search for and select the first minimally satisficing decision solution that can be identified. If the decision maker is unhappy with the outcome of the chosen solution, the decision maker will engage in sequential search among alternatives until an alternative is identified that generates satisfactory outcomes (Simon, 1945). As was true of the rational model, the issues associated with problem definition are also not addressed by the satisficing model of decision making. Although the satisficing model accounts for changes in decision alternatives, it, too, takes the problem definition stage as being non-problematic. Therefore, like the rational model, the problem definition stage is taken as a given in the decision making process. As a consequence, issues of problem redefinition are not raised.

The Incremental Model

According to the incremental model of decision making (Lindbloom, 1959; Quinn, 1980), problem redefinition is a result of a series of small, piecemeal changes in the decision solution. The incremental model is the first to consider problem redefinition issues. However, the model does not discuss the circumstances when problem redefinition is taken as a planned and deliberate step in the decision making process. This is a serious limitation of this model because a decision to undertake problem redefinition is qualitatively different from making a series of incremental changes that eventually lead to a problem redefinition.

A number of authors have provided examples of organizations where problem redefinition had to be considered as a planned and deliberate change (Nystrom and Starbuck, 1984; Hedberg, Nystrom and Starbuck, 1976). Johnson (1988) points out that the retail firm that he analyzed experienced some relatively clear breaks in strategy during the duration of his longitudinal investigation. Although problem redefinition may result from a series of incremental changes, the incremental model does not identify the determinants of the situation which will cause incremental change to result in a redefinition of the problem. It is possible for incremental change to occur without leading to problem redefinition (Johnson, 1988).

The strategic management literature, which was discussed the previous chapter, provides many examples of situations where incremental change does not lead to problem redefinition. One such example is Johnson's (1988) study of retail firms. In this study, changes in the environment resulted in a decrease in one retail firm's profits. Managers responded to these decreases by implementing strategic changes. Although the situation demanded a redefinition of the problem or change in strategy, Johnson (1988) points out that all the changes were within the bounds of the organization's current strategy: the merchandizing of the product. Johnson concludes that the incremental changes the managers had implemented did not lead to problem redefinition for this firm.

The Cybernetic Model

An alternative to the rational model, the cybernetic model addresses a number of issues the other decision making models do not. Specifically, the cybernetic model, like the satisficing and incremental models, accepts the thesis that humans have bounded rationality (Abelson and Levi, 1985). As a consequence, the cybernetic model proposes that human beings tend to resort to routine behavior whenever possible as a way to save on cognitive efforts (Abelson and Levi, 1985; Steinbruner, 1974; Bateson, 1972).

According to the cybernetic model, decision makers attend to two feedback loops (Ashby, 1952). The first loop gives the decision makers information about the critical variables the decision maker monitors in order to assess whether or not the decision solution chosen is effective (Steinbruner, 1974). The critical variables are those variables that are essential to determining the effectiveness of a given decision solution in the current environment (Ashby, 1952). When the values of the critical variables fall outside acceptable ranges, the decision maker will need to choose a new decision solution from the same set of viable alternatives identified by the present definition of the problem.

The second feedback loop gives the decision maker information about the decision situation, itself. According to Ashby's (1952) conception of cybernetic theory, the decision situation is defined by variables that characterize the boundaries or the 'state' of the situation. Steinbruner (1974) calls these the 'state' variables of the decision situation. Only a few variables are monitored due to people's bounded rationality (Simon, 1945). People monitor these variables in order to assess the validity of their definition of the situation (Steinbruner, 1974; Powers, 1973a; b; Ashby, 1952). Any changes in the characteristics of the state variables are signals to the decision maker that the decision situation has changed and, therefore, a change in the definition of the decision is indicated. In other words, decision makers use the changes that occur in the characteristics of the state variables as criteria when deciding whether or not to institute a change in the definition of the problem.

The strategic decision making literature postulates that strategists engage in a process that is analogous to the cybernetic concept of state variable monitoring when assessing the appropriateness of the current organizational strategy. Specifically, in times of uncertainty, strategists undertake the activity of environmental scanning (Fahey, King and Narayanan, 1981; Fahey and King, 1977). Environmental scanning requires strategic decision makers to monitor and interpret social, political, economic and technological variables in the environment. This activity is undertaken in an attempt to determine if the organization's strategy "fits" with its current and future environment (Daft, Sormunen, and Parks, 1988). A function of organizational strategy is to define the problem that the environment creates for the organization. This function of organizational strategy is similar to the function of problem definition for individual decision makers. Dyer (1985) notes that external (i.e., environmental) events and crises precipitate change far more often for organizational strategy than do planned events. For example, Fox (1984) points out how General Motors did not undertake strategic change until environmental contingencies forced it to change. Smart and Vertinsky (1984) asked 94 managers from 94 firms to respond to a survey which asked them how they would strategically respond to different environmental scenarios. Their results showed that managerial choices of strategies were dependent on specific environmental characteristics. As proposed by the cybernetic model, the strategic decision making literature suggests that decision makers monitor specific variables in the environment to determine if the current strategy is the correct one (Fahey and King, 1977; Dyer, 1985; Daft et al, 1988). When the environmental variables indicate a change is needed, the literature proposes that strategists should and often do change the strategy of the organization (Johnson, 1988).

The idea that there are environmental state variables that people monitor in order to assess the validity of their problem definition leads to the question of how people come to know which state variables to monitor in a given situation? Steinbruner (1974) argues that people's implicit theories direct attention to specific state variables. Simon (1945) also stipulates that the decision making process is initiated by stimuli which channel attention in definite directions. Specifically, he notes that this stimuli directs attention to selected aspects of the situation. This function of people's implicit theories has been noted by other researchers as well (Cowan, 1986; Stephans, 1985; Weick, 1979; Neisser, 1976).

Jacoby, Chestnut, Weigl and Fisher (1976) did a study which provides empirical evidence of the function of people's implicit theories in information acquisition. These researchers presented subjects with a simulated shopping situation and asked the subjects to purchase a brand from among those displayed. Their results revealed that most subjects did not seek additional information on different brands when making their purchase decision. Rather, they relied on their memory, implicit theories and experience about the products in making their purchase selection. This study highlights the importance of individuals' implicit theories in the selection of information used in a decision making situation.

Research described in the strategic decision making literature has found that the information that managers collect from their environmental scanning activities is interpreted in terms of their own cognitive understanding of the world (Johnson, 1988). Several researchers argue that managerial assumptions play a crucial role in the collection and interpretation of environmental information (Daft and Weick, 1984; Hambrick and Mason, 1984; Shrivastava and Mitroff, 1984). The strategic decision making literature provides further theoretical support for the proposition that decision makers' implicit theories guide their attention to specific state variables when they are attempting to monitor the effectiveness of their current problem definitions.

The cybernetic model takes decision making theory a quantum leap forward by incorporating the idea that the definition of the problem may need to be consciously changed as part of the decision making process. However, the cybernetic model makes the assumption that people will automatically institute problem redefinition when the appropriate state variables change. As theoretical and empirical investigations by Volkema (1986), Mausch (1985), Nystrom and Starbuck (1984), and Staw (1976) point out, people often do not change their definitions of the problem even when the state variables are at extreme values. If the environment changes but decision makers continue to identify the problem with the prior definition, decision makers run the risk of committing the error of solving the wrong problem (Volkema, 1986; Raiffa, 1968). The cybernetic model cannot explain this breakdown in the routine decision making process.

The Cybernetic Process: A Cognitive Perspective

Steinbruner (1974) attempts to correct this weakness of the cybernetic model by integrating cognitive principles with the cybernetic model. In his revised model, Steinbruner (1974) contends that the mind imposes the definition on the problem based on previous experiences. The cognitive activity of defining a problem is time-consuming and expends considerable effort. In order to save time and cognitive effort, a person may simply ignore or cognitively distort information on state variables that call for a change in the definition of the problem so that, in effect, no change is indicated.

Steinbruner's (1974) revision of the cybernetic decision making model raises an interesting question. Specifically, if decision makers naturally tend to try to maintain their current problem definition in an effort to conserve on cognitive energy, what determinants lead them to actually undertake problem redefinition? This is an important question because, as discussed earlier, decision makers do undertake conscious and planned changes in their definitions of the situation (Johnson, 1988). The following section presents a model of Problem

Redefinition. This model will form the basis for generating hypotheses about possible determinants of a decision maker's choice to institute a change in problem definition.

A Model Of Problem Redefinition

As stated in the preceding section, given that decision makers try to minimize the amount of cognitive energy they spend on a decision situation, what factors influence the decision makers to consciously implement a redefinition of the problem? The central feature of the Problem Redefinition model proposed here is the incorporation of human information processing variables into the decision making process as factors of problem redefinition.

The empirical and theoretical significance of information processing variables has been established in various areas of research such as attribution theory and the study of heuristics. Due to their bounded rationality, it is widely accepted that decision makers have limited information processing capabilities (Simon, 1945). However, this does not diminish the importance of the information processing function in the decision making process.

The information processing approach to problem solving has been viewed as highly applicable to decision behavior (Abelson and Levi, 1985). Walsh (1987) notes that managers face ill-structured and complex problems with limited information processing capabilities. According to O'Reilly (1983), information and the ability to process it are of particular importance in the decision making situation. A number of researchers have argued that nonroutine, uncertain decision tasks, like most tasks faced by top managers, require extensive information processing (Daft et al, 1988; Culnan, 1983; Daft and Macintosh, 1981; Tushman and Nadler, 1978). Abelson and Levi (1985) state that the processing of information for the purpose of making a decision is one of the fundamental steps a decision maker faces. Indeed, the decision making stage of problem definition is fundamentally an information processing task (Cowan, 1986; O'Reilly, 1983).

The rules decision makers use for processing information are defined as part of their implicit theories. These information processing rules provide decision makers with ways of dealing with ill-defined situations that could otherwise lead to conflict and stress (Abelson and Levi, 1985). Due to bounded rationality, decision makers cannot cognitively process all available information in the environment and, therefore, must screen out the information they need in order to make a decision (Simon, 1945). Information processing rules allow decision makers to screen out relevant information in ambiguous decision situations (Schwenk, 1984). These rules direct the decision makers' attention to information that their past experience has indicated is relevant to the specific type of decision situation. It is argued here one of the primary factors of decision makers' decision to institute problem redefinition is the way that they use information processing rules to process that information gathered on the decision situation.

Although there has been increasing recognition of the importance of information processing to the decision process, current decision making theories do not provide extensive insight into how people compile and interpret information they have gathered on their state variables before making a problem reformulation decision. Payne et al (1978) contend that this lack of understanding is due to the traditional focus on the end product of the decision process as opposed to other stages of the decision making process (i.e., the problem definition, search for alternatives, and evaluation of the alternatives stages).

In the information processing literature, most of the research investigating decision makers' information processing activities has focused on identifying the information processing rules, or heuristics, that influence the choice of decision solutions (e.g., Tversky and Kahneman, 1974; Hogarth, 1981). The majority of these studies have been conducted in a laboratory context (Tuggle and Gerwin, 1982). So, there is a question of their generalizability (Schwenk, 1984; Ungson, Braunstein and Hall, 1981). Taylor (1982) argues t hat the utility of information processing rules can be increased if they are grounded in more general behavioral theories. There is also growing empirical evidence from research conducted in field settings that these information processing rules are used in the real world (Schwenk, 1988).

Only recently has there been a theoretical application of the research on information processing rules to the issue of how these rules affect the initial problem definition of ill-defined managerial decisions (Barnes, 1984; Schwenk, 1984). These researchers discuss how cognitive processes of decision makers relate to the way they identify and formulate a problem. To date, however, no empirical research has investigated what cognitive factors lead decision makers to decide whether or not to implement problem redefinition.

Although the decision making literature on the information processing component of the problem redefinition stage is sparse, literature from a number of other disciplines may be used to identify important information processing rules that may be adapted to address this important issue. For example, attribution theory is a rich source of principles that appear to be useful for addressing this particular problem redefinition issue. Research on the heuristics decision makers use to choose from among decision solution alternatives also provides theoretical and empirical propositions for understanding how people compile and interpret information on state variables. This literature will be specifically adapted to apply to the issue of problem redefinition.

Changes in the Characteristics of the State Variables

As proposed by the cybernetic theory of decision making, it is hypothesized that decision makers have a set of state variables that they use to assess the validity of their definition of the situation (Steinbruner, 1974; Ashby, 1952). Decision makers keep track of these state variables to ascertain whether or not the decision situation has changed (Steinbruner, 1974; Powers, 1973a; b). In other words, decision makers have a set of state or decision variables which they use to define the situation (Van de Van, 1986). If the situation changes, the characteristics of the state variables will change (Ashby, 1952). Decision makers who monitor their state variables will then change their problem definition accordingly. It is argued here that information processing rules which facilitate and/or reinforce the process of monitoring these state variables will also facilitate problem redefinition when it is appropriate. Based on the literature review presented below, the following information processing rules are proposed: whether the state variables are observed first or last in a sequence of decision information, the vividness of the state variables relative to other observed variables and the consistency of the state variables' characteristics over time. Each of these four information processing rules will be discussed in detail below.

Primacy

The order in which the state variables are observed in a sequence of decision information should have implications for the effect of any particular change in state variables on problem definition change. Kelly and Michela (1980) define the primacy effect as that situation where a person makes a judgement based on some initial information and then ignores or distorts all succeeding information, although relevant, to conform to the initial judgement. In other words, the first information a person receives is given more weight in making a decision than any succeeding information.

Research from attribution theory provides empirical evidence that the order of observation of information, specifically performance data, may influence the compilation and interpretation of that information. A study by Ross, Lepper and Hubbard (1975) demonstrated the primacy effect of information. Their subjects were required to read 25 cards, each of which had a false and real suicide note. The subjects were required to identify which were the real suicide notes. The experimenters gave the subjects false performance feedback at the completion of the task. After a time interval, the subjects were debriefed thoroughly and were told that the performance feedback was false. At the conclusion of the debriefing, the subjects were asked to rate their actual performance and their ability to do tasks similar to the experimental one. Results of the data analyses showed that the subjects' ratings exhibited an impact of the false feedback inspite of the extensive debriefing. In this study, subjects weighted the initial information more than the succeeding information they received during the debriefing session. Several other studies by the authors replicated and expanded upon these findings (Anderson, Lepper and Ross, 1980; Jennings, Lepper and Ross, 1980; Lepper, Ross and Lau, 1980; Anderson and Ross, 1978).

A study that compared the ascending and descending orders of performance and the effect on subsequent attribution provides further empirical support for the primacy variable. Jones, Rock, Shaver, Goethals and Ward (1968) found that subjects made different attributions when correct answers were given by the observed person mainly during the first fifteen of thirty problems than when the correct answers were given for the last fifteen. This study clearly shows how the order of information can change people's decisions, in this case, their attributions for observed behaviors.

The literature from attribution theory provides considerable evidence that decision makers are more likely to weigh information they see first in a sequence of observed information more than when that information is not perceived first. The primacy information processing rule affects subsequent attributions for behavior. In a more generic sense, attribution research suggests that when people make a decision, information presented first is likely to be weighted more than information presented subsequently.

The primacy information processing rule has also been associated with various personnel decisions that managers have to make. In that portion of the personnel literature which focuses on human judgement errors in personnel processes, the first impression error is similar to the concept of primacy (Nisbett and Ross, 1980). Wexley and Latham (1980) define first impression error as a tendency of a manager to make an initial favorable or unfavorable judgement about an employee and then ignore subsequent information about the employee to support his or her initial impression of that person. In other words, when making a personnel decision, the decision maker gives the most weight to that information seen first in a sequence of information.

Wexley and Latham (1980) point out that first impressions are often evident in managers' ratings of their employees' performances. Murphy, Balzer, Lockhart and Eisenman (1985) found evidence for a primacy effect in performance appraisals. Subjects were exposed to worker performance which was manipulated to be either good or bad. This initial information about performance had a significant effect on subjects' subsequent ratings of the worker. Again, performance information that was presented first to the subjects was weighed more than subsequent performance information.

The notion of a primacy effect has also been investigated in the personnel selection literature. Specifically, first impression, or primacy, has been found to play a dominant role in interview judgments (Springbett, 1958). Farr and York (1975) asked 72 college recruiters to read descriptions of hypothetical applicants and then evaluate each applicant. They found evidence of a primacy effect in recruitment decisions when an interviewer had to make a single judgment during the interview.

In another study which looked at the effect of primacy on decision making, Tucker and Rowe (1979) had subjects read and evaluate interview transcripts after looking at a letter of reference. They found that the information presented first had a greater effect on subjects' subsequent decisions about the extent to which the people they observed should be held responsible for their performance. Again, the effect of initially perceived information on subjects' subsequent judgments is evident.

In a similar design, Dipboye, Fontenelle, and Garner (1984) had half their student interviewers review the interviewee's application before the interview while the other half did not. The students who had a preview of the application had lower total accuracy in their recall of application items. In this study, the results suggest that information presented first was given more weight in memory than information presented later. Dipboye, Stramler and Fontenelle (1984) reported similar findings. Rasmussen (1984) also found a first impression effect for subjects who previewed a resume before observing the interviewee. In the preceeding studies the results suggest that information that is presented first is given more weight by decision makers than information presented later.

This discussion highlights the prevalence of the primacy information processing rule in various decision making situations. Both the attribution and the personnel literatures provide considerable empirical evidence to support the argument that decision makers tend to give more weight to information they see first in a sequence of information in their decision making process.

These findings may be applied to the current research study. The studies discussed above would suggest that a change in a state variable will have a greater impact on a decision maker's decision to implement problem redefinition when that state variable is presented to the decision maker first in an information stream. In other words, changes in the state variable are more likely to lead to changes in problem definition if the decision maker observes the state variable first in a series of information variables.

Recency

The studies presented above suggest that an information variable observed first will be given the most weight when making decisions. Other studies suggest the existence of a recency effect of information (Nisbett and Ross, 1980). This information processing rule proposes that people are influenced most by the last set of information they are exposed before making decisions (Kelley and Michela 1980). Nisbett and Ross (1980) report that recency effects are found most often under certain circumstances. Jones and Goethals (1972) propose that these circumstances are a) memory constraints that favor recall of information presented later; b) circumstances producing strong contrast effects; and c) objectives or processes which have the capacity to change over time so that later information, if it's implications are different from that of early information, may be perceived as more valid.

The attribution literature has found some support for the recency information processing rule. In particular, Feldman and Allen (1975) found that when subjects were given graphical presentations of a person's entire performance pattern, a recency effect occurred. The last set of performance information presented was used most by the study's subjects when they were asked to make attributions of intelligence for the person.

The recency effect has also received empirical support from the personnel literature. In a study by Farr and York (1975), the researchers found a recency effect when their interviewers were asked to make repeated judgments during an interview. The results of the study found that, in this situation, the interviewers based their judgments on the most recent information given to them.

An interesting illustration of the recency effect is found in the literature focusing on eyewitness accounts. As Loftus (1979) notes, research has found that post-incident information updates the original memory of the incident. Bekerian and Bowers (1983) argue that there is evidence that people have a pre-existing bias that favors access of the most recent and relevant memory. Loftus, Miller and Burns (1978), Bekerian and Bowers (1983) and Bowers and Bekerian (1984) all conducted empirical investigations to assess the impact of PEI on subjects' recollections of original information about the event. All three studies found a recency effect for the PEI information when that information provided subjects with non-redundant information. The empirical evidence from the PEI studies suggests that people have a tendency to weigh more recently presented information more than previously observed information.

A research study by Cooksey and Freeboy (1987) explicitly investigated the influence of subsequent cue perceptions on judgmental accuracy after accounting for the effect of an initial set of cues. Specifically, they had 20 student teachers review 118 student profiles to judge student reading achievement. The subjects were given cues from two domains: demographic and cognitive (i.e., verbal aptitude scores). The authors performed a hierarchical multiple regression where the demographic cues were entered first. Cooksey and Freeboy argued that demographic information was most likely to be observed by the teacher first and cognitive information was more likely to be gathered at a later date. The results found that there was a general trend for the cognitive cues to account for four times as much unique variance than the demographic factors. Again, the more recently observed information had a greater effect on subjects' judgement.

Based on the research cited above, it is proposed that when the state variable which provides evidence for change is viewed last, it will be given more weight by the decision maker than if it had been observed earlier in a sequence of information. Under this condition, it is expected that decision makers will be more likely to implement problem redefinition.

The order of observation hypotheses raise the question as to which order effect, primacy or recency, has the greater impact on the way people process information. Nisbett and Ross (1980) argue that primacy is the pervasive effect. Furthermore, they contend that recency effects are rare and, if found, are most often due to experimental manipulations. However, they do not provide supporting empirical evidence for their contention. The issue is still open to debate. This research will investigate the separate effects of the primacy and recency information processing rules on decision makers' problem redefinition decisions.

Vividness.

Another information processing variable which may affect decision makers' judgments about the need to implement problem redefinition may be the visual vividness of the state variable the decision maker observes. Research in attribution theory has found evidence that the vividness of an object is likely to change the attributions made to that object. Ross and Anderson (1982) remark that the most researched area in attribution theory is the relationship between attention and the perceptual and cognitive factors that mediate attention.

The research on the vividness information processing rule suggests that whenever some aspect of the environment is made disproportionately vivid to the perceiver, that aspect is given more weight in the causal attribution. The importance of vivid events lies in the fact that perceptually vivid events are more readily remembered than nonvivid events (Abelson and Levi, 1985; O'Reilly, 1983; Nisbett and Ross,1980). Vividness of information exerts a disproportionate impact on inferences (Nisbett and Ross, 1980). According to Nisbett and Ross (1980), information that may be described as vivid is likely to attract and hold attention and to excite the imagination. For this reason, vivid information is recalled and weighed more in a decision situation.

In most attribution studies, visual vividness has been the most frequent operationalization of the theoretical concept of salience (Ross and Anderson, 1982). As Abelson and Levi (1985) point out, perceptual vividness or dramatic impact is an intuitively appealing characterization of the underlying operative variable of salience.

A series of studies by McArthur and Post (1977) substantiate the considerable influence of a variable's visual vividness on observers' attributions of causality. The authors did several experiments to test the effect of vividness on observers' attributions. In one experiment, the researchers had people observe a two-person dialogue where a brighter light was focused on one of two the people. Visual salience or vividness was operationalized as the relative brightness of the light on one person versus the other person. In another experiment, one of two people was in motion when the subjects observed the situation. In this experiment, visual vividness was operationalized as a person moving versus a person in a stationary position. Once they had observed the visually manipulated situation, the subjects were then asked to make attributions for the focal (the visually vivid) person's behavior in the dialogue to either the situation or the person's disposition. Attributions for the focal person's behavior were made more to the situation than to the person. In another experiment, McArthur and Post had one male actor in a female group. Again, observers' attributions for the focal actor were more situational than for the other members of the group.

Ross and Fletcher (1985) note that these results show people giving greater weight to variables that stand out visually relative to those variables that do not when they make attribution decisions. From these studies, it is possible to conclude that the vividness information processing rule appears to have an impact on the decisions people make.

In a variation of the McArthur studies, Taylor, Fiske, Etcoff and Ruderman (1978) had observers make attributions for group members. Visual vividness was achieved by creating unique racial or gender status of a group member in a group. Their findings revealed that the fewer the number of group members from a given gender category or racial group, the more prominent the observers judged those people to be. This is similar to the findings of McArthur and Post (1977).

The preceding literature review suggests that visual vividness is a variable of theoretical and empirical importance in the information processing function. Adapting this principle to the current decision making research, it is expected that a visually vivid state variable indicating a need for change is more likely to lead to a change in a decision maker's current problem definition than a nonvivid state variable.

Consistency.

The norm of consistency is a concept with great social value (Pfeffer, 1981). As Pfeffer (1981) and Staw

(1976) note, consistent behavior is weighed more positively than inconsistent behavior when people make judgments about others. Staw (1981) postulates that a lay theory may exist in society that people who are consistent in their actions are better leaders than those who switch from one line of behavior to another. O'Reilly (1983) also notes the existence of a "consistency bias" in human behavior. Several prominent psychological theories of human behavior theorize about the human tendency to actively seek consistency in everyday functioning (Walters and Marks, 1981).

Staw and Ross (1980) did a study to specifically study the existence of a lay consistency theory. The subjects were given a case describing the behavior of an administrator. The administrator in the case initially received negative information about organizational performance results. The subjects were given information about the subsequent organizational performance where conditions of consistency and success were experimentally manipulated. Subjects were asked to rate the performance of the administrator. Results indicated that the administrator was rated highest when the case indicated that the administrator had followed a consistent course of action. The results also revealed a significant interaction effect between success and consistency. Staw and Ross (1980) conclude that individuals can become committed to a course of action simply because they believe consistency in action is the appropriate form of behavior.

Some of the strongest supporting evidence of Staw and Ross' conclusion comes from the literature on escalation of commitment. Managers often will not change a failing strategic direction that they have previously committed to because of the general social belief that leaders should behave in a consistent manner (Gray and Ariss, 1985). In fact, the failure of a given policy may lead them to become even more committed to that policy (Staw, 1976). As Donaldson and Lorsh (1983) note, with reputations and egos on the line, managers are strongly disposed to give strategies time to prove themselves and are willing to tolerate a shortfall in performance as long as the results may be ultimately acceptable. Staw and his associates (Staw, 1976; Staw and Fox, 1977; Staw and Ross, 1978; Ross and Staw, 1986) have done a number of studies which have found the escalation of commitment phenomena under various experimental conditions. One of the primary reasons for the escalation of commitment is the norm of consistency (Staw, 1981).

The norm of consistency would suggest that decision makers are not likely to change their problem definition in an effort to remain consistent in their behavior. However, behavior does change (Staw and Ross, 1978) and problems are redefined (Walsh, 1987; Cowan, 1986). The norm of consistency may play a role in these decisions to institute change. Prior research and theory suggest that people value consistency in behavior (Pfeffer, 1981; Staw, 1976). People also value information when it is consistent with their expectations (Higgins and Bargh, 1988).

A further extension of the norm of consistency is proposed here. It is argued that people may value information that is consistent in and of itself when they are making decisions. In other words, when people are given information that consistently informs them that the situation has changed, they are likely to give that information more weight due to the norm of consistency. Based on this rationale, it is proposed that the more the characteristics of the state variable provide consistent indications of a need for change across time, the more likely the decision maker is to make changes in their definitions of the problem.

Summary

Previous decision making research has not focused much empirical investigation on the topics associated with problem redefinition in a decision making situation. This study proposes to specifically investigate the issue of what factors lead decision makers to implement problem redefinition. It was argued that the way people process and assess the information that they gather on the state variables they monitor to determine problem definition validity may identify relevant factors. Reviews of literature from several different research fields suggest four important information processing variables which might affect decision makers' decisions to implement or not to implement problem redefinition. Based on this literature, it is expected that a change in a state variable is more likely to lead a decision maker to initiate a change in problem definition if the state variable is viewed first in a sequence of information variables, last in a sequence of information variables, vivid relative to other information variables, and if the state variable indicates a consistent need for change over time.

The Model of the Determinants of Problem Redefinition.

The model of Problem Redefinition that is presented below is based on the theoretical framework of the cybernetic model of decision making. This model is primarily an integration of cognitive information processing rules suggested by the preceding literature review with the second feedback loop of the cybernetic decision making model.

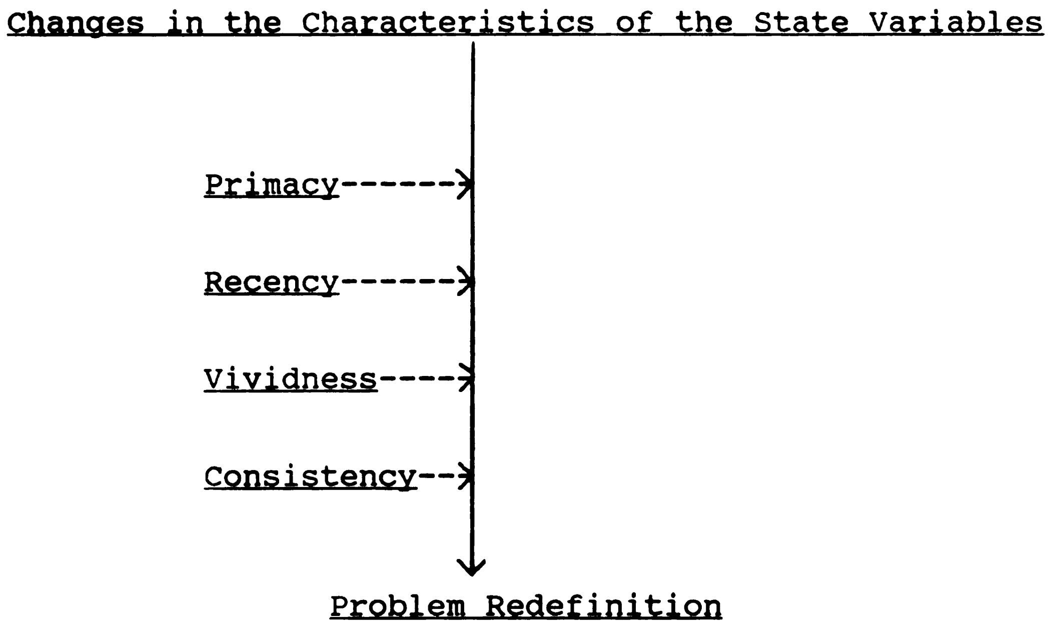

FIGURE 1: THE PROBLEM REDEFINITION MODEL

HYPOTHESES

The dependent variable of interest in the present research is a decision maker's decision to undertake problem redefinition. The independent variable is the change in the characteristics of the state variables--those variables that describe the state of the decision situation. The information processing variables, recency, primacy, vividness and consistency over time, are expected to interact with the independent variable to effect the dependent variable.

Hypothesis 1

Decision makers will change their definition of the problem to the extent that the characteristics of the state variable indicate a need for this change.

Hypothesis 2

H2a: A change in the state variable is more likely to lead to problem redefinition when the state variable is presented first in a sequence of information.

H2b: A change in the state variable is more likely to lead to problem redefinition when the state variable is presented last in a sequence of information.

H2c: A change in the state variable is more likely to lead to a change in the definition of the problem when the state variable is visually vivid relative to other variables in an information stream.

H2d: A change in the state variable is more likely to lead to a change in the definition of the problem when the change in the state variable is consistent over time.

CHAPTER TWO

METHODOLOGY

This chapter begins with a description of a model used in strategic management, the Product Market Movement model. The Product Market Movement model is a theoretical model of the dynamic strategic process any product undergoes over time. The model will be used to design the decision situation for this research. This presentation of the model is followed by a description of the subject population and research design. A brief summary of the pilot studies followed by the operationalization of the Problem Redefinition model variables is found in the next section. The chapter concludes with a discussion of the data analyses techniques used.

AN APPLICATION OF THE PROBLEM REDEFINITION MODEL TO THE PRODUCT MARKET MOVEMENT MODEL

In order to test the model presented in Figure 1, it is necessary to create a research condition where subjects are faced with a dynamic decision situation which has characteristics that change over time. The work of Neisser (1976), Weick (1979) and Nisbett and Wilson (1979) would suggest that subjects are likely to approach the same decision situations in different ways because of different life experiences and, therefore, different implicit theories. This indicates that it is necessary to provide subjects with the same cognitive theories in order to control for different life experiences and, thus, differential subject responses to changes in the decision situation. The major purpose of creating a research situation with these constraints is to be able to test the effects of the above hypothesized determinants of problem redefinition on actual decisions to redefine the problem while controlling for the biases of different life experiences.

A theory from strategic management, the Product Market Movement model, will be used to set up the research situation. The Product Market Movement (PMM) model, which is adapted from the Product Life Cycle model (Porter, 1980), identifies a dynamic situation which requires corresponding changes in the decision maker's definition of the situation. The PMM model proposes that the market of a product follows a pattern of change similar to the stages of human development. According to the PMM model, a change in the product's market stage should result in a change in decision policy by members of the market. The PMM model identifies a decision situation where problem redefinition (in the form of strategic reformulation) is necessary for the decision makers to continue to be successful in the marketplace. This, then, creates a research situation that allows the Problem Redefinition model presented in Chapter One to be tested.

There are other factors about the PMM model that make it compatible with the Problem Redefinition model. First of all, the PMM model can be used to provide decision makers with a single theory that specifies the state variables that decision makers should use to assess the validity of their problem definitions or strategy. The PMM model provides a detailed description of the state variables that identify the product's market and their characteristics for each stage of the market. The PMM model thus serves the same function that individuals' implicit theories do in everyday decision situations: to guide the implementation of problem redefinition when it is indicated.

The second similarity between the PMM model and the Problem Redefinition model is also a function of the implicit theories that decision makers use. For both models, decision makers are expected to implement new problem definitions or strategies when the characteristics of the state variables change. The PMM model gives the decision maker an explicit theory about what actions the decision makers should take in order to address each new change in the market. This, too, is similar to the function of the individuals' implicit theories in most decision making situations.

Third, each time the market state changes, the state variables undergo significant changes in characteristics. These changes should alert the decision makers to a need to implement a new strategy or problem definition. This is parallel to the cybernetic theory notion of the second feedback loop in decision making. The second feedback loop of cybernetic decision making is comprised of information gathered on the characteristics of the state variables monitored by the individual decision maker to assess problem definition validity.

A detailed description of the PMM model follows. An understanding of the model should give the reader a clearer idea of how this model will be used as a tool to set up a research situation in which decision makers will be faced with a dynamic situation and still have a common theory to guide them through the decision process. This will enable a test of the effects of the above hypothesized information processing rules on decision makers' problem redefinition decisions.

The PMM

The PMM model hypothesizes that a company with a particular product is faced with a market that is dynamic and changes with time. According to the PMM model, the market goes through three distinctly different problem stages: Introduction, Growth/Maturity, and Decline (Hofer, 1975; Day, 1971). The PMM lays out operating and strategic contingencies for each stage of the cycle (Bourgeois, 1984). In each stage, the characteristics of the market are different. Different decision policies must be implemented in order that a company operating within that market be successful (Hofer, 1975).

The Introduction phase of the PMM is often designated as the beginning of the market. According to Hofer (1975), an emphasis is placed on drawing buyer attention to the business and its products through advertisement. In addition, there is an emphasis on research and development activities (Fox, 1973). In this stage, product prices tend to be high and the competitors are few (Wasson, 1974).

In the early parts of the Growth/Maturity stage, the products are assumed to have gained consumer recognition. Now, the emphasis is on expanding the firm's market share through early Growth stage activities such as capital investments in production and marketing (Anderson and Zeithaml, 1984), product and process modifications and innovations (Porter, 1980), and shift toward mass distribution (Hofer, 1975). The key function during the early Growth/Maturity stage is marketing. The price of the product is still high but is lower than it was in the

Introduction phase because the production process has started to become more refined. For this reason, the product starts to cost less to produce. Finally, competition is increasing during this stage as additional rivals enter the growing market and this, too, tends to keep product prices down.

The primary strategic objective of firms during the latter part of the Growth/Maturity phase of the market is to defend brand position against competing brands (Anderson and Zeithaml, 1984). This objective is mainly achieved through product improvements and distribution approaches (Hofer, 1975). The influx of new competition has generally stabilized in this stage and there is some stability in market growth (Porter, 1980). Due to the stability in market growth, competition for market share is intense (Wasson, 1974). Managers attempt to increase market share through brand differentiation (Anderson and Zeithaml, 1984). Although sales remain stable, managers are encouraged to increase net cash flow by decreasing production costs (Hofer, 1975). Due to the highly competitive nature of the market, price wars are possible and the first shakeouts of competitors occur as a result (Fox, 1973). Firms moving into a mature market from a Growth stage should not rely solely on incremental adjustments to strategy if they want to remain effective (Glueck, 1972). Firms must be aggressive in this fiercely competitive stage.

In the Decline stage of the product's market, the company can harvest, take a leadership position, develop a niche as its strategy, or exit the marketplace entirely (Porter, 1980). When harvesting, the firm divests its financially weak operations and continues to build on its strengths. In a leadership role, the firm tries to increase its market share. A firm may create a strong position in a segment of the market and defend its niche. Or, a firm may simply sell out. What the decision maker decides to do will depend on the characteristics of the market and the firm's own competitive strengths (Harrigan, 1979). The major strategic objective of this stage is to realize all possible profits from the firm's operations that the firm can (Wasson, 1974). By this time the market has gone through several shakeouts, so the number of rivals has probably decreased (Fox, 1973). Accurate sales forecasts are very important for the company to be able to determine at which point it is most profitable to phase out operations (Fox, 1973; Wasson, 1974).

The above description of the PMM model highlights the need for the strategist within a particular industry to attend to changes in the characteristics of the state variables that indicate a change in the market stage. The state variables identifying the market's stage in the PMM model serve the same function as the state variables in the cybernetic framework. A change in the characteristics of the state variables related to market stage should lead a decision maker to redefine the PMM stage. This redefinition should be operationalized by a change in strategy that emphasizes those organizational functions relevant to the new PMM stage.

There have been criticisms of the PMM model. Namely, as Porter (1980) points out, the stages do not always hold across product markets. Second, the length of the cycles of the PMM also may vary across markets. Third, the nature of the competition may be different for the different stages across different product markets. Finally, companies have been known to extend their Growth/Maturity cycles beyond expected limits due to their Growth strategies.

While being aware of these limitations of the PMM model, it is important to point out that what is being tested here is not the viability of the PMM model itself. Rather, the PMM is an <u>application</u> of the problem redefinition model presented earlier and will be used as a means for operationalizing that model. Specifically, the theory behind the PMM will be taught to the subjects in the research to provide them with a theory about the way to redefine the PMM stages they will encounter during the course of the life cycle of their product's market. The theory will also identify which state variables decision makers should attend to when they are assessing the validity of their current problem definition or strategy. Like the Problem Redefinition model presented in Chapter One, the PMM model presents the subjects with dynamic decision situations that change over time. These changing situations require corresponding changes in the decision makers' definitions of the situation.

THE RESEARCH METHOD

In the next section of this chapter, the discussion will center around the description of the design of the research investigation.

The Research Instrument

Decision making processes have primarily been studied by three different techniques: archival research (e.g., Allison, 1969), verbal protocols (e.g., Ericsson and Simon, 1979), and computer algorithms (e.g., Svenson, 1979; Kleinmuntz, 1975). There are a number of problems associated with each one of these techniques (see Schwenk, 1985; Cummings, 1982; Lichtenstein, 1982; Payne, 1982, Posner, 1982; Tversky, 1982; Hogarth, 1980). Due to the numerous problems with the methods commonly used to study decision making empirically, the method for creating meaningful PMM decision situations used here was a computer simulation. The computer simulation was programmed to create a market situation which followed the principles of the PMM model over time. Subjects were asked to operate a company in this dynamic industry according to the principles of the PMM model.

Computer simulations have an advantage in that they can simulate social contexts in a manner that increases the similarity between the research setting and actual field settings without losing extensive experimental control (Schwenk, 1985). Furthermore, computer simulations can also allow investigation of the decision making process in a dynamic context that is more ecologically valid for the PMM model than the static research design used in most decision making research (Abelson and Levi, 1985; Cummings, 1982). As Schwenk (1984) argues, in order to achieve generalizability from laboratory investigations of decision making processes, it is necessary that the decision makers be allowed to learn from their tasks. In addition, the research design should allow subjects to make numerous decisions and receive continuous feedback after the decisions have been made (MacCrimmon, 1982). Computer simulations are flexible enough to construct such a research situation. These simulations also enable the researcher to compress time in order to recreate decision situations that would naturally extend over long periods of time in the a field setting (Wexley and Latham, 1981). In short, computer simulations allow the development of a decision situation that has a history, consists of interdependent decision problems, incorporates the entire decision process and forces the problem definition to change with changes in the environment. These are some of the fundamental characteristics of real decisions (Pondy, 1982). And, as Pondy (1982) notes, it is difficult to study these characteristics in the field. However, the computer simulation will allow these characteristics to be replicated in a laboratory situation where there is greater experimental control.

The Subjects

Business policy undergraduate students were asked to participate in a computer simulation as part of their course requirement. Each subject was asked to do 100 decision iterations. Since the study design was a within subject design, ten students comprised the sample.

The Design

There were two stages to the research project: the pilot studies and the actual data collection stage. Five pilot studies were conducted. The purpose of the pilot studies was to assess the computer simulation to ensure that all programming bugs were found and corrected before the actual data collection phase. In addition, the pilot studies were used to assess the feasibility of the work requirements from the subjects. Results of these pilot studies are reported in a later section of this chapter.

During the first stage of the project, subjects were introduced to the PMM model and theory through a class lecture and their reading of Porter's (1980) discussion of the PMM model. Subjects were informed about the industry level variable, average industry sales, that was the state variable for the simulation. The lecture informed the subjects about the characteristic of the state variable, the slope of the industry sales curve, for each stage of the PMM model. Specifically, subjects were informed that the industry average sales curve usually started out flat but slowly increased during the Introduction, increased rapidly and then leveled off during the Growth/Maturity stage and decreased sharply during the Decline stage. Subjects were cautioned that not all industries followed the PMM model perfectly. Therefore, the product market presented in the simulation could experience decreases in Growth or increases in Decline and other such reversals.

The subjects were also told, in detail, which organizational functions should be emphasized during each of the PMM stages. They were provided with the theoretical reasoning underlying the relationships between a particular PMM stage and its associated organizational functions. This theoretical reasoning was presented in the second section of this chapter which described the PMM model for the reader.

The latter part of the lecture was devoted to informing the subjects about the simulation, per se. The subjects were told that they would be the chief executive officer (CEO) of a firm for which they would be making strategic decisions. The firm would be a start-up operation and would run 25 years or 100 decision time periods. The subjects were introduced to the organizational functions they would be making resource allocations for. The subjects were informed that their strategy would be identified by the way they chose to allocate resources to eight organizational functions: research and development, marketing research, distribution, plant and equipment, production development, accounting control, quality control and advertising. The subjects were told whether their resource allocations to each function should be low, medium or high for each of the three PMM stages. Another strategic decision that subjects were required to make was to set the price of the product. Again, subjects were informed about the expected range of the price of the product for each PMM stage. The researcher also told the subjects that there was a time lag for the impact of their allocations on their performance. The time lag was programmed into the simulation to enhance its real-world replication. Most real-world allocations do not have an immediate effect on company performance. It takes time before the impact is evident in company performance. Finally, subjects were told they would be given feedback on their net and gross incomes as well as industry average sales. It was pointed out to the subjects that their allocation decisions would affect their net and gross incomes. However, they were informed that the effect of their allocations on industry level sales would not be evident to them since sales were calculated on an industry-wide basis.

All of this information is part of the PMM model described in section two of this chapter. The information provided subjects with an explicit PMM theory needed to guide their simulation decisions. Subjects were told that the closer they followed the PMM theory's prescriptions for price setting and resource allocations, the better their simulation performance would be. Subjects were informed that their grades would be based on their relative effectiveness in maximizing their company's total earnings by the end of the simulation. In this way, an attempt was made to make the outcome of the subjects' decisions in the simulation meaningful to them.

At the conclusion of the lecture, subjects were asked to complete a consent form releasing their simulation results to the researcher for use in this research. Subjects were also warned against discussing their strategies with other subjects. Since subjects were to be graded on their simulation performance relative to the performance of other subjects, they were cautioned that sharing of information would hurt their grades. The researcher was present in the computer room while subjects were engaged in the simulation and deliberately intervened when there was any possibility of information being shared between subjects.

The second phase of the research design consisted of the subjects' actually doing the computer simulation. The final phase involved a debriefing session where subjects were able to discuss their experiences with the simulation and were shown how to integrate the content of the PMM with the process of the simulated situation. In addition, the subjects were given a chance to comment on the simulation itself. The debriefing concluded with a summary of the research project.

The Simulation

The computer simulation used for data collection purposes was designed to test the subjects' abilities to apply the PMM theory in a simulated business environment.

At the beginning of the computer simulation, subjects were given graphic information and feedback on industry average sales, which was the state variable, and on their own net and gross incomes. For subsequent iterations, these feedback graphs were presented at the beginning of each decision iteration. After viewing this information, the subjects were presented with a computer screen that listed all eight organizational functions. Since this was a start-up operation, there were no resources allocated to any of the eight functions when the subjects started the simulation at time 1. Each organizational function did have a maximum amount that could be allocated to it during any one decision time period, and the minimum amount of allocation permitted to any organizational function was zero. The simulation required subjects to specify the amount of money they wanted to allocate to each function, including a 0 allocation.

Once the subjects made their allocation decisions, the computer generated numerical feedback on their individual sales, gross income, net income, and total cumulative earnings/losses. This feedback was a function of their resource allocation decisions. As stated earlier, in order to make the simulation more representative of a real organization, the resource allocations did not immediately impact individual sales, gross or net income. In other words, subjects did not immediately realize the impact of their allocation decisions. Industry average sales, which were not a function of subjects' resource allocation decisions, were also presented at this time.

At the end of the feedback, subjects were asked to specify, on a scale of 1 to 7, the extent to which they thought their firm was on the right track. For this scale, 1 indicated "not at all" and 7 indicated "to a great extent." At this point, for each of the 100 decisions, subjects were given the option to discontinue the current session of the simulation until a later time. Each new decision iteration started with a display of the three feedback graphs. The simulation continued as described above. This whole process was repeated for the subsequent 98 decision iterations.

The Five Pilot Studies

Five pilot studies were performed using 85 business students. The purpose of these studies was to test the functionality and the duration of the computer simulation as well as its overall feasibility. In general, the pilot studies followed the research design specified above. Subjects took an average of 10 hours a person to complete the 100 decisions which represented 25 years.

Based on the results of the pilot data, several process changes were made in the simulation itself. Specifically, subjects were asked to keep track of their decisions as a precaution against possible loss of data due to technological failure (e.g., during one pilot study, the power in the computer center shut down). Another process change was to cut the number of decision iterations from 200 to 100 because of time and subjects' patience constraints and fatigue.

In addition to these process changes, several changes were made in the simulation, per se. These included such things as re-specifying the weights for various relationships between the variables. This increased the impact of allocation decisions made by subjects on outcome variables. It was also discovered that subjects were basing their inferences of the PMM stage on the time period of the simulation they were in. In order to minimize this, the PMM model was programmed to have unexpected peaks and troughs over the course of the 100 iterations. Since research on the PMM model has found that the PMM stages may reverse themselves (Porter, 1980), the peaks and troughs programmed into the current simulation are in line with the theoretical context of the PMM model. In essence, the main function of the five pilot studies was to test the feasibility of the entire research design with particular emphasis on the simulation.

The Operationalized Problem Redefinition Model

Each one of the variables specified in the Problem Redefinition model presented in Figure 1 had to be operationalized. The model in Figure 2 presents the operational version of the Problem Redefinition model (Figure 1, Chapter One).

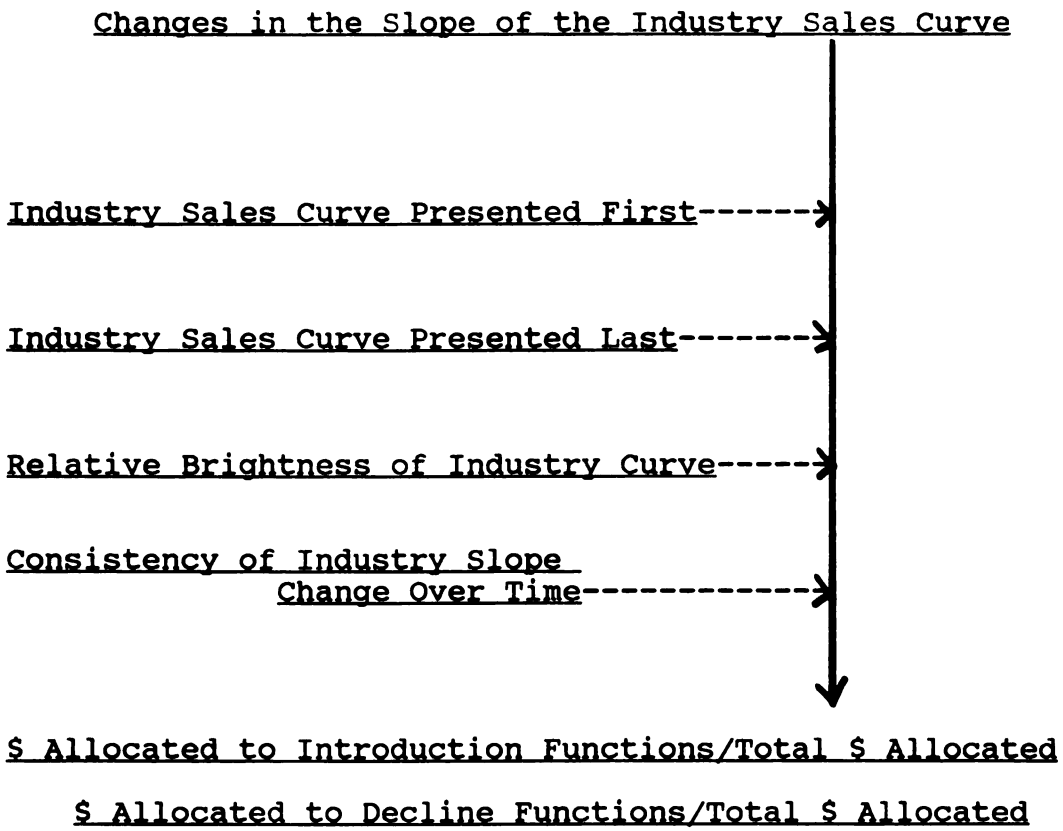

Figure 2

AN OPERATIONAL VERSION OF THE PROBLEM REDEFINITION MODEL

The next section will present an in-depth discussion of each variable presented in Figure 2, the operationalized model of Problem Redefinition.

Operationalizing the Variables

All variables were measured at each time period for each subject.

The Independent Variable

The PMM State Variable

The PMM state variable emphasized for this simulation, as shown in Figure 2, was industry average sales. This was the variable that the decision makers received information on before they started each allocation decision. The characteristic of the state variable that was emphasized here was the industry sales' slope because, in the present simulation, it indicated the market's stage. This characteristic of the state variable was operationalized as the slope of the curve relating industry sales with time: sales at time t minus sales at time t-1.

In cybernetic terms, average industry sales slope, in its function as a state variable, defined the stage or state of the PMM cycle. Specifically, when the average industry sales slope was going up rapidly, the market was in the Introduction stage. When the slope flattened, the market was in the Growth stage. Finally, when the industry sales slope was decreasing rapidly, the market was in the Decline stage.

The primary purpose of this investigation was to study how information processing variables influenced the impact of the change in the state variable characteristics on the dependent variable, problem redefinition. For this reason, only one state variable was used in the current research design. Use of more than one state variable would require the development of an extensive theoretical and empirical framework to account for the statistical interactions among the state variables and each of the information processing variables as well as the effect of each of these on the dependent variable. Since this was not the focus of the research and, in adherence to the rule of parsimony, subjects were given feedback on only one state variable, average industry sales, and on two company level performance variables, company gross and net incomes. As will be discussed in detail shortly, the latter types of information were necessary to operationalize the recency and primacy information processing rules.

Due to the time series nature of the market sales, it was expected that the independent series, average industry sales slope, would be characterized by high autocorrelation. Autocorrelation is a characteristic of most time series data because each error term is often correlated with the error term or terms immediately before it (McCain and McCleary, 1978; Neter, Wasserman and Kutner, 1985). In order to eliminate this source of autocorrelation in the average industry sales slope, industry sales were regressed on time, $time^2$, $time^3$, and $time^4$ (the relationship between time and average industry sales had been constructed to conform to a 4th order equation). An industry sales slope measure then was constructed from differences in residual average industry sales (time t minus time t-1), that is, sales net of the defined effects of time.

The Interaction Variables

Primacy and Recency of the State Variable

Students received graphic feedback on average industry sales, their own net and their own gross incomes. The order in which the state variable, a graph of average industry sales, was presented to subjects changed over time to operationalize the primacy and recency variables. The graph of the average industry sales curve was randomly presented first (of the 3 feedback graphs) across the 100 iterations. Similarly, the graph of the average industry sales curve was randomly presented last (of the 3 feedback graphs) across the 100 iterations. This condition was also allocated randomly across the 100 iterations.

In order to statistically analyze the primacy effect, P1, a dummy variable was created. To create P1, the variable was coded 1 if the industry sales graph appeared first, 0 otherwise. To analyze the recency effect, another dummy variable, R1, was created. If the average industry sales graph appeared last, R1 was coded 1, 0 otherwise.

Vividness of the Criteria

The industry average sales curve was made visually vivid by programming three lines to overlap instead of the single line curve of the other feedback graphs. The industry average sales curve was visually vivid 50 of the 100 iterations. And, as with the previous variables, this condition was allocated randomly across the 100 iterations.

In order to test for the effect of the levels of this variable, a third dummy variable, V1, was created. When the average industry sales slope was highlighted, V1 was coded 1, 0 otherwise.

Consistency of Criteria

Consistency, C1, was operationalized as the number of increases or decreases in the average sales curve over the past 5 time periods. C1, therefore, had a range from 0 to 5.

The consistency variable was created by counting the number of increases (or decreases) of the average industry sales curve over the previous five time periods. For example:

Consistency	Industry Sales
-	225
-	300
-	400
-	500
5	600
5	800
1	700
1	1050

Time

Only decisions during iterations 7-100 were assessed since it was expected that subjects would take several time periods before allocating resources in ways compatible with the Introduction phase of the PMM. Also, there were no consistency values available for t1-t6 because of the way C1 was operationalized. In addition, since the resource allocations that subjects made were programmed to have a lagged effect, subjects did not receive any feedback on their firm's performance during these time periods.

Since the relationship between average industry sales and time was a curvilinear function, linear regression would not adequately capture this non-linear relationship. Therefore, it was necessary to divide the decision iterations into two sets. The first set consisted of iterations 7-53. The relationship between average industry sales and time was generally positive during this time frame. The second set was comprised of iterations 54-100. A negative relationship existed between average industry sales and time during this time period.

The Dependent Variables

Ratios of Resource Allocations

The dependent variables were the actual allocation of resources subjects made to organizational functions. Two indices were formed to operationalize the dependent variables during the Introduction and Decline phases. The first index was the Introduction ratio. The Introduction ratio was computed at each time period for decision periods 7-53 in the following manner:

INTRODUCTION RATIO (t) = ($ Allocated to Market Research + Research & Development)/ (Total $ Allocated to All Functions)

The Decline ratio was computed at each time period for decision periods 54-100 in the following manner:

DECLINE RATIO (t) = ($ Allocated to Quality Control+ Plant&Equipment + Advertising)/ (Total $ Allocated to All Functions)

The relative amount allocated to the functions associated with the Growth/Maturity stage is possible to determine by these two indices. To determine the amount allocated to the Growth/Maturity stage, the sum of the amounts allocated to the Introduction and Decline functions needs to be subtracted from the total amount of resources allocated by the subject. Therefore, for this study, the Growth/Maturity stage did not constitute a distinct dependent variable.

It was expected that the dependent series would be autocorrelated. Since subjects allocated resources as a function of their perception of which stage of the PMM they were in and since the average industry sales slope was the indicator of the PMM stage, the percent of resources allocated to any particular function was expected to be autocorrelated. This autocorrelation was a function of the autocorrelation in the average industry sales slope series. In an effort to eliminate the dependent series' autocorrelation, the regression of industry sales on time, described earlier, was used to generate expected values of industry sales as a function of time. Expected values for industry sales slope as a function of time were then calculated (expected industry sales value at time t minus expected industry sales value at time t-1). The percent funds allocated to each allocation ratio was then regressed on the expected industry sales slope variable, and the dependent variables were taken to be the <u>residual</u> values for the percent funds allocated <u>net</u> of the effects of the expected value of the industry sales slope. By eliminating the effect of the source of the autocorrelation in the dependent variable, the slope of the industry sales curve, the autocorrelation in the dependent variable was decreased.

The data for the Decline allocation ratio was not analyzed for time periods 7-53 since the subjects were specifically told that the computer simulation would be based on the PMM model. The PMM model stipulates that Decline allocation decisions should not be made during the Introduction and Growth phases of the PMM cycle. For the same reasons, the data for the Introduction allocation ratio was not analyzed for time periods 54-100.

Summary

Subjects were expected to pay close attention to the state variable, the slope of the industry sales curve, to the extent that the graph of sales over time was presented under the following conditions: it was first or last, it was vivid or it exhibited consistency over time. No interactions among these four conditions were hypothesized. It was expected that subjects would adhere more closely to the allocation patterns prescribed by the PMM under these conditions.

THE STATISTICAL ANALYSIS

The Baseline Model

The following baseline model was estimated for each subject for both the Introduction and the Decline allocation ratios:

$$\frac{\%\ \$\ \text{Introduction (Decline)}}{\text{Total } \$ \text{ Allocated}} = A1 \frac{\text{*Industry Sales}}{\text{Slope at } t} + C$$

For the Introduction allocations, during time periods 7-53, it was expected that A1 would be statistically significant and have a negative value. In other words, the proportion of resources allocated to the Introduction functions relative to total allocations was expected to decrease as the rate of average industry sales increased.

The proportion of resources allocated to organizational functions in the Decline phase relative to total expenses during time periods 54-100 was expected to increase with declining rates of average industry sales. Note that the amount of resources allocated to the Decline functions was not expected to increase. But, the amount allocated to all other functions was expected to decrease. So, the Decline ratio was expected to increase. For these reasons, A1 for the Decline baseline model is expected to be statistically significant and also have a negative value.

The Control Model

The variables of theoretical interest for this model were the interaction of the information processing variables with the state variable. Consequently, it was necessary to assess the impact of the main effects and other control variables on resources allocation decisions before calculating the impact of the interaction terms. Therefore, the following control model containing only main effects was estimated for each subject once for the first time period for the Introduction allocation ratio. The control model was estimated a second time for the second set of time periods for the Decline allocation ratio. The control model is as follows:

$$\frac{\%\ \$\ \text{Introduction (Decline)}}{\text{Total}\ \$\ \text{Allocated}} = \begin{aligned}[t] & A1 * \text{Industry Sales} \\ & \text{Slope at } t\ + \\ & A2*P1\ + \\ & A3*R1\ + \\ & A4*V1\ + \\ & A5*C1\ + \\ & A6*C1(T-1)\ + \\ & A7*C1(T-2)\ + \\ & A8*C1(T-3)\ + \\ & A9*C1(T-4) + \text{Constant} \end{aligned}$$

where,

P1 is the primacy main effect
R1 is the recency main effect
V1 is the vividness main effect
C1 is the consistency main effect.

As described earlier, the consistency term was computed by counting the pattern of the changes in slope for the preceding five time periods. Because of the way it was constructed, the consistency variable was characterized by fifth-order autocorrelation. Therefore, the control model specified above was expanded to include C1 (t-1), C1 (t-2), C1 (t-3), C1 (t-4).

Assessing the Impact of the Interaction Terms

In order to test the impact of the interaction of the information processing variables with the state variable on the resource allocation decisions, each interaction term was independently added to the control model presented above for each subject for both sets of time periods. In other words, the effect of each interaction term was assessed separately from the effect of any other interaction term.

Assessing the Impact of Primacy

It was hypothesized that subjects would pay more attention to the average industry sales slope data when these data were presented first. It was expected, then, that the impact of the industry sales slope at time t on the two dependent variables would be greater when this condition held. This was assessed by adding an interaction term, industry sales slope at t * P1, to the control equation.

<u>Assessing the Impact of Recency</u>

It was hypothesized that subjects would pay more attention to the industry sales slope data when these data were presented last. It was expected, then, that the impact of the industry sales slope at time t on the two allocation ratios would be greater when this condition held. This was assessed by adding an interaction term, industry average sales slope at t * R1, to the control equation.

<u>Assessing the Impact of Vividness</u>

It was hypothesized that subjects would pay more attention to the industry sales slope data when the industry average sales feedback graph had a vivid curve than otherwise. It was expected, then, that the impact of the industry sales slope at time t on the percent funds for Introduction (Decline)/Total $ allocated would be greater when this condition held. This was assessed by adding an interaction term, industry sales slope at t * V1, to the control equation.

<u>Assessing the Impact of Consistency</u>

It was hypothesized that subjects would pay more attention to the industry average sales data when the data were consistent than when they were not consistent. The impact of the industry sales slope at time t on the Introduction and (Decline allocation) ratios was expected to be greater when this condition held. This was assessed by adding an interaction term, industry average sales slope at t * C1, to the control model.

The Complete Model

The complete model specified by the hypotheses was as follows:

```
% Funds for Introduction=A1 * Industry Sales Slope at T +
(Decline)                A2*P1 +
Total $ Allocated        A3*R1 +
                         A4*V1 +
                         A5*C1 +
                         A6*C1-1 +
                         A7*C1-2 +
                         A8*C1-3 +
                         A9*C1-4 +
                         A10*Industry Sales Slope at T*P1;
                         A11*Industry Sales Slope at T*R1;
                         A12*Industry Sales Slope at T*V1;
                         A13*Industry Sales Slope at T*C1+
                         Constant
```

The terms A2 to A9 were included as controls. The coefficients of theoretical interest were A10 to A13. Since P1, R1, and V1 were randomly distributed across time, they were not expected to be correlated with each other or with C1. Therefore, sorting out the simultaneous effects of each of the added interaction terms was not expected to be a problem.

Determining the Significance of the Impact of the Interaction Variables

Following the recommendations of Cohen and Cohen (1983), the impact of each interaction term was analyzed by testing for the significance of the change in R^2 as the interaction terms were each individually added to the control model. The following formula was used to compute the F-value (Cohen and Cohen, 1983; Marsden, 1981):

$$F = \frac{(R^2_{ci} - R^2_{c})}{(1 - R^2_{ci})} \times \frac{n - k_c - k_{ci} - 1}{k_{ci}} \qquad df = k_{ci}, n - k_c - k_{ci} - 1$$

where,

c= the control model
ci= the control model with the interaction term.

Determining the Direction of the Impact of the Interaction Variables

In order to understand the conditional relationship between the dependent and independent variables, the regression equation is written as:

Eq. 1: Y = I + B1 X1 + B2 X2 + B3 X1*X2

where:

Y= the Introduction or Decline Allocation Ratio

X1= the main effect of the information processing variable

X2= the industry sales slope

I= intercept

B1= beta for the main effect of the information processing variable

B2= beta for the industry sales slope variable

B3= beta for the interaction term

Eq. 1 may be rearranged as follows when X1 and X2 are both continuous variables (Cohen and Cohen, 1983; Pedhauzer, 1982; Marsden, 1981):

Eq. 2: $Y = (B2 + B3\ X1)\ X2 + (B1\ X1 + I)$

According to Cohen and Cohen (1983), this rearrangement allows the interaction effects to be interpreted in conjunction with the main effects of the interacting variables. This reordering also clarifies the conditionality of the effects of a focal variable on the other variables. For this example, the (B2 + B3 X1) term is the slope and the (B1 X1 + I) term represents the Y intercept. This structure of the regression equation indicates that the regression of Y on X2 depends on the value of X1. Cohen and Cohen (1983) and Marsden (1981) both recommend that three representative lines be examined, one for a "low" value of X1 (1 standard deviation below the mean), one for a "medium" value of X1 (at the mean), and one for a "high" value of X1 (1 standard deviation above the mean). Such a set of representative lines varies both in slope and in intercept.

Equation 1 may be rearranged in the following manner when X1 is a dichotomous variable and X2 is a continuous variable:

Eq. 3 (for X1=1): $Y = (B2 + B3)\ X2 + (B1 + I)$

Eq. 4 (for X1=0): $Y = B2\ X2 + I$

In the case of Equation 3, the slope of the regression line is the (B2 + B3) term and the Y intercept is represented by the (B1 + I). The slope of the regression line in Equation 4 is the B2 term and the Y intercept is represented by I.

It is necessary to examine the T-values of the interaction term as well as the T-values for main effect of the dummy coded variable when the interaction has a dummy coded term (Pedhauzer, 1982). The dummy coding results in creation of two separate groups: one experiencing the effect X1 and the other not. A significant T-value for a main effect indicates that there is a significant difference in the intercepts of the regression lines of the two groups. A difference in intercepts signals that there is a difference in the means for the Y variable for the two groups.

In an effort to understand the conditional relationships revealed by the change in R^2 analysis, the analyses illustrated in equations 2, 3 and 4 will be applied to each subject for each interaction term in a regression model where the change in the R^2 was significant.

There are three types of effects an interaction may have on the relationship between the dependent and the independent variable (Pedhazur, 1982). The first effect is that of no interaction. This situation is usually characterized by parallel regression lines and the differences between the two conditions is accounted for entirely by the differences between the two intercepts. The second type of interaction effect is an ordinal interaction. In this situation, the two lines have different intercepts indicating a difference in means between the two conditions. However, this difference between the two conditions decreases over increasing values of the independent variable due to a difference in the slopes of the regression lines. With ordinal interaction, the regression lines may move closer together but they will not cross within the observed range of the independent variable. Disordinal interaction occurs when the regression lines of the two conditions do cross. This means that one condition has a greater effect for some values of the independent variable while the other condition has a greater effect for other independent variable values.

To decide whether an interaction is ordinal or disordinal, one must consider the value of the independent variable at which the lines cross each other (Pedhazur, 1982). If the value lies within the observed values of the independent variable, the interaction is disordinal. However, if the value is outside the observed range of the independent variable, the interaction is considered to be ordinal (Pedhazur, 1982). Cohen and Cohen (1983) provide a simple formula to determine the point of crossing:

$$X_C = -B_1 / B_3$$

This point will be calculated for each subject for each interaction term that is significant to help determine what type of interaction effect is evident.

The major focus of this analysis is the interpretation of the conditional information each interaction term provides about the regression of each allocation ratio on the industry average sales slope. The most efficient approach to interpretation is to examine the direction of the changes that occur in the slope of the regression lines (i.e., whether increasing or decreasing) as the value of the interaction term is increased from low to high.

Summary

This chapter has described the Product Market Movement model, a strategic decision making model which presents a framework for a dynamic strategic problem. This model was used to create the decision situation for this research investigation. The subject population and the research design were described. The final section presented a detailed description of the statistical analysis conducted.

CHAPTER THREE

RESULTS

This chapter reports the results of the data analyses conducted to empirically investigate the hypotheses of this study. First, the descriptive statistics for the independent variables will be presented. Then, the intercorrelations among the independent variables will be reported. The results of the regression analyses for each of the ten subjects will be discussed in light of the specific hypotheses of this study.

Descriptive Statistics

Table 1 presents the sample sizes, means and standard deviations of the slope after it has been adjusted for autocorrelation. It also presents the descriptive statistics for the primacy, recency, vividness, consistency main effects and interactions for time periods 7-53. Table 2 presents the same descriptive statistics for the same variables for time periods 54-100.

TABLE 1

Means and Standard Deviations for the Independent Variables
(Time 7-53)

	N	Mean	SD
Industry sales slope (ISS)	46	-9.01	192.80
Primacy (P)	47	.40	.50
Recency (R)	47	.34	.48
Vividness (V)	47	.53	.50
Consistency (C)	47	2.53	1.57
Primacy*Slope (P*ISS)	46	-23.89	99.24
Recency*Slope (R*ISS)	46	-10.51	118.97
Vividness*Slope (V*ISS)	46	-2.64	118.30
Consistency*Slope (C*ISS)	46	-36.29	407.45

As was explained in Chapter Two, the first six observations were dropped from the analysis. Furthermore, the time series data were split at the point where the relationship between industry average sales and time went from positive to negative. The purpose of this action was to do two separate regression analyses on the data set since linear regression is inappropriate to examine curvilinear relationships. This split left 47 observations in each data set. The industry sales slope variable was created by taking the differences of the industry average sales net of time. All analyses were conducted on the remaining 46 observations.

TABLE 2

Means and Standard Deviations for the Independent Variables
(Time 54-100)

	N	Mean	SD
Slope (ISS)	46	-15.12	205.24
Primacy (P)	47	.57	.50
Recency (R)	47	.21	.41
Vividness (V)	47	.47	.50
Consistency (C)	47	3.02	1.66
Primacy*Slope (P*ISS)	46	-18.12	155.91
Recency*Slope (R*ISS)	46	13.87	112.79
Vividness*Slope (V*ISS)	46	-21.43	141.43
Consistency*Slope (C*ISS)	46	-32.62	621.35

In order to correct for any implicit weighting problem that may occur due to the differences in standard deviations among the independent variables, all the main effects of the independent variables were standardized to a mean of 10 and a standard deviation of 1. The interaction terms were created after the standardization of all the main effects.

TABLE 3

Means and Standard Deviations for the Standardized Independent Variables (Time 7-53)

	N	Mean	SD
Slope (ISS)	46	10.00	1.00
Primacy (P)	47	10.00	1.00
Recency (R)	47	10.00	1.00
Vividness (V)	47	10.00	1.00
Consistency (C)	47	10.00	1.00
Primacy*Slope (P*ISS)	46	99.97	12.31
Recency*Slope (R*ISS)	46	100.07	13.65
Vividness*Slope (V*ISS)	46	99.82	14.12
Consistency*Slope (C*ISS)	46	99.61	13.16

TABLE 4

Means and Standard Deviations for the Standardized Independent Variables (Time 54-100)

	N	Mean	SD
Slope (ISS)	46	10.00	1.00
Primacy (P)	47	10.00	1.00
Recency (R)	47	10.00	1.00
Vividness (V)	47	10.00	1.00
Consistency (C)	47	10.00	1.00
Primacy*Slope (P*ISS)	46	100.16	13.51
Recency*Slope (R*ISS)	46	100.31	15.97
Vividness*Slope (V*ISS)	46	100.06	13.16
Consistency*Slope (C*ISS)	46	99.78	14.15

Intercorrelations Among the Standardized Independent Variables and the Interaction Terms

The intercorrelations among the standardized independent variables, slope, primacy, recency, vividness and consistency, and the interaction terms for time periods 7-53 are reported in Table 5 for the standardized variables. The intercorrelations for the same variables are reported for 54-100 in Table 6.

Table 5

INTERCORRELATIONS AMONG STANDARDIZED INDEPENDENT VARIABLES AND INTERACTION TERMS (Time 7-53)

	1 ISS	2 P	3 R	4 V	5 C	6 P*ISS	7 R*ISS	8 V*ISS	9 C*ISS
1	(1.00)								
2	-.21	(1.00)							
3	-.08	-.59++	(1.00)						
4	.02	-.01	.13	(1.00)					
5	-.05	-.11	.22	.27*	(1.00)				
6	.62++	.63++	-.55++	.02	-.11	(1.00)			
7	.68++	-.59++	.67++	.13	.14	.06	(1.00)		
8	.70++	-.15	.05	.72++	.13	.44***	.55++	(1.00)	
9	.69++	-.22	.12	.19	.69++	.37***	.59++	.61++	(1.00)

*p< .10
**p< .05
***p< .01
+p< .001
++p< .0001

The intercorrelations reported in Table 5 for the independent terms slope, primacy, recency, vividness and consistency for time periods 7-53 show a significant negative correlation between the primacy and recency variables (r= -.59). The direction of the relationship is not surprising. Although the correlation between recency and primacy is significant (p< .0001), it does not make theoretical sense to collapse the two variables into one variable. There is also a significant relationship between the main effects of consistency and vividness (r= .27). However, this relationship is not highly significant (p< .07).

The significant correlations among the various interaction terms are not unexpected since the terms share a common variable, average industry average sales slope.

TABLE 6

INTERCORRELATIONS AMONG STANDARDIZED INDEPENDENT VARIABLES AND INTERACTION TERMS
(Time 54-100)

	1 ISS	2 P	3 R	4 V	5 C	6 P*ISS	7 R*ISS	8 V*ISS	9 C*ISS
1	(1.00)								
2	-.09	(1.00)							
3	.20	-.60++	(1.00)						
4	-.14	.20	.03	(1.00)					
5	.04	-.04	-.01	.20	(1.00)				
6	.67++	.67++	-.33**	.03	.04	(1.00)			
7	.77++	-.47+	.78++	-.08	.01	.21	(1.00)		
8	.65++	.07	.17	.65++	.19	.54++	.53+	(1.00)	
9	.71++	-.05	.13	.05	.73++	.50+	.52+	.57++	(1.00)

*p< .10
**p< .05
***p< .01
+p< .001
++p< .0001

In Table 6 the only significant relationship for main effects reported is between the primacy and recency variables (r= -.60). Again, the correlation is in the expected direction. For the reasons stated earlier, the effect of these two variables was assessed independently.

Again, as with the data presented in Table 5, the significant relationships among the interaction terms are not unexpected since the terms share a common variable, the industry average sales slope.

Test of the Hypotheses

The hypotheses proposed in Chapter One are presented below:

Hypothesis 1:

Significant changes in decision makers' definitions of the problem will occur to the extent that the characteristics of the state variable indicate a need for this change.

Operationally,

Significant changes in the subjects' allocations to functions of a particular PMM stage relative to total expenditures will occur to the extent that the slope of the industry average sales curve indicates a need for this change.

Hypothesis 2

The probability of a change in the definition of the problem will increase to the extent that the state variable changes and is

H2a: first,
H2b: last in presentation order,
H2c: vivid,

H2d: the change is consistent over time

Operationally,

The probability of a change in allocation patterns to functions of a given PMM stage relative to total expenditures will increase to the extent that the slope of the industry average sales curve indicates a need for change and is

H2a: presented first of three feedback graphs,
H2b: presented last of three feedback graphs
H2c: highlighted relative to the other two graphs
H2d: consistently negative or positive over time

The Results of the Multiple Regression Analysis of the Baseline Model

Hypothesis One proposes that subjects will change their allocations to the extent the industry average sales slope indicates that there is a need for such a change. The baseline model will be calculated for each subject to test this hypothesis. As described in the discussion on statistical analyses in Chapter Two, the baseline model is as follows:

% $ Introduction (Decline)/=A1*Industry Sales Slope at t +
Total $ Allocated Constant

Table 7 presents the summary statistics for the regression analysis of the baseline model for each of the 10 subjects for time periods 7-53. Table 8 reports the same statistics for time periods 54-100.

TABLE 7

SUMMARY OF REGRESSION ANALYSIS OF THE BASELINE MODEL
(Time Periods 7-53)

Introduction Ratio			
S	R^2	F	P
1	.05	2.29	.14
2	.00	.06	.80
3	.00	.02	.89
4	.00	.20	.66
5	.00	.11	.74
6	.03	1.29	.26
7	.01	.47	.50
8	.00	.08	.78
9	.00	.31	.58
10	.00	.11	.74

TABLE 8

SUMMARY OF REGRESSION RESULTS FOR THE BASELINE MODEL
(Time Periods 54-100)

Decline Ratio			
S	R^2	F	P
1	.00	.00	.95
2	.02	.64	.43
3	.03	1.18	.28
4	.03	1.34	.25
5	.00	.01	.98
6	.00	.09	.77
7	.02	.72	.40
8	.02	.82	.37
9	.00	.02	.89
10	.01	.51	.48

The results from Tables 7 and 8 indicate that Hypothesis One is not supported. It appears that subjects did not change their allocations to PMM functions for a given stage due to corresponding changes in the slope of the industry sales curve.

The Results of the Statistical Analysis Assessing the Impact of the Interaction Terms

A two-step process was used to test the effect of the interaction terms on resource allocation decisions (Hypothesis Two). First, a control model, as shown below, was computed for each subject for both sets of time periods. A total of five regression equations were run for each resource allocation ratio. The dependent variable was regressed on the main effects and control variables for the first regression. This was the Control model. The control model is as follows:

```
% $ Introduction (Decline)=A1*Industry Sales Slope at t +
      Total $ Allocated      A2*P +
                             A3*R +
                             A4*V +
                             A5*C +
                             A6*C(t-1) +
                             A7*C(t-2) +
                             A8*C(t-3) +
                             A9*C(t-4) + Constant
```

where,

P is the primacy main effect
R is the recency main effect
V is the vividness main effect
C is the consistency main effect.

Second, for the four other regression equations, the dependent variable was regressed on all the variables included in Control model and one interaction term at a time. For example, the second regression equation consisted of the Control model and the Primacy interaction term. The third regression equation was the Control model and the Recency interaction term. As may be recalled from the description of the statistical analysis in the previous chapter, the impact of the interaction terms on the resource allocation decisions was assessed by comparing the change in R^2 when each interaction term was independently added to the control model. The interaction terms are represented in the subsequent tables in the manner reported below:

PRIM-slope*primacy
REC-slope*recency
VIV-slope*vividness
CON-slope*constancy.

The results are reported in Tables 9 and 10. The first column identifies the subject. The second column presents the F-value for the regression equation assessing the Control model. All the columns labeled "P" present the significance of the preceding values. The R^2 change columns indicate the increase in R^2 that occurs when a specific interaction term is added to the Control model.

TABLE 9

SUMMARY OF RESULTS OF REGRESSION ANALYSES FOR THE CONTROL AND INTERACTION MODELS

INTRODUCTION EXPENSES

(Time 7-53)

SS	Control	P	R^2	Prim	P	R^2	R^2 Change	P	Rec	P	R^2	R^2 Change	P	Viv	P	R^2	R^2 Change	P	Con	P	R^2	R^2 Change	P
1	1.88	.09	.34	1.74	.11	.35	.01	ns	1.64	.14	.34	.00	ns	1.64	.14	.34	.00	ns	1.64	.14	.34	.00	ns
2	1.95	.08	.35	1.77	.11	.36	.01	ns	1.77	.11	.36	.01	ns	1.79	.10	.36	.01	ns	1.75	.11	.35	.00	ns
3	1.74	.12	.32	1.80	.10	.36	.04	ns	1.55	.15	.33	.01	ns	1.60	.15	.33	.01	ns	1.60	.15	.33	.01	ns
4	1.63	.15	.31	1.63	.14	.34	.03	ns	1.43	.21	.31	.00	ns	1.50	.18	.32	.01	ns	1.53	.17	.32	.01	ns
5	1.84	.10	.33	1.86	.09	.38	.05	ns	1.61	.15	.33	.00	ns	1.65	.14	.34	.01	ns	1.66	.13	.34	.01	ns
6	1.69	.13	.32	1.81	.10	.36	.04	ns	1.59	.17	.33	.01	ns	1.48	.19	.32	.00	ns	1.48	.19	.32	.01	ns
7	2.15	.05	.37	2.30	.04	.42	.05	ns	1.88	.09	.37	.00	ns	1.94	.08	.38	.01	ns	1.92	.08	.38	.01	ns
8	2.15	.05	.37	2.20	.04	.41	.04	ns	1.93	.08	.38	.01	ns	1.91	.08	.37	.00	ns	1.91	.08	.37	.00	ns
9	1.41	.22	.28	1.60	.15	.33	.06	ns	1.26	.29	.28	.00	ns	1.32	.26	.29	.01	ns	1.29	.28	.29	.01	ns
10	1.62	.15	.31	1.60	.15	.33	.02	ns	1.44	.21	.31	.00	ns	1.44	.21	.31	.00	ns	1.43	.21	.31	.00	ns

TABLE 10

SUMMARY OF RESULTS OF REGRESSION ANALYSES FOR THE CONTROL AND INTERACTION MODELS

DECLINE EXPENSES

(Time 54-100)

SS	Control	P	R^2	Prim	P	R^2	R^2 Change	P	Rec	P	R^2	R^2 Change	P	Viv	P	R^2	R^2 Change	P	Con	P	R^2	R^2 Change	P
1	.77	.64	.17	.76	.66	.19	.02	ns	.86	.58	.21	.03	ns	.76	.66	.19	.02	ns	.68	.74	.17	.00	ns
2	1.28	.28	.26	1.64	.14	.34	.08	.05	1.14	.36	.26	.00	ns	1.33	.26	.29	.03	ns	1.38	.24	.30	.04	ns
3	1.22	.32	.25	1.21	.32	.27	.02	ns	1.47	.20	.31	.06	ns	1.07	.41	.25	.00	ns	1.82	.10	.36	.11	.05
4	.96	.49	.21	.85	.59	.21	.00	ns	1.02	.45	.24	.03	ns	1.26	.29	.28	.07	ns	.86	.58	.21	.00	ns
5	.43	.91	.11	.82	.61	.20	.09	.05	.70	.71	.18	.07	ns	.41	.93	.11	.00	ns	.99	.47	.24	.13	.05
6	1.29	.28	.26	1.45	.21	.31	.05	ns	1.40	.22	.30	.04	ns	1.25	.30	.28	.02	ns	1.64	.14	.34	.08	.05
7	.35	.95	.09	1.87	.02	.37	.28	.01	.68	.74	.17	.08	ns	.60	.80	.16	.07	ns	.41	.93	.11	.02	ns
8	1.33	.26	.27	1.16	.35	.27	.00	ns	1.65	.14	.34	.07	ns	1.16	.35	.27	.00	ns	1.61	.15	.33	.06	ns
9	.50	.86	.12	.57	.83	.15	.03	ns	.62	.79	.16	.04	ns	.44	.92	.12	.00	ns	.94	.51	.23	.11	.05
10	.64	.76	.15	.99	.47	.24	.09	.05	.89	.55	.22	.07	ns	.57	.82	.15	.00	ns	.73	.69	.19	.04	ns

An examination of Table 9 reveals that the inclusion of any one of the four information processing interaction variables, primacy, recency, vividness or consistency, does not significantly increase the R^2 for any of the subjects' Introduction allocation decisions during time periods 7-53.

For the Decline allocations, during time periods 54-100, as shown in Table 10, the addition of the primacy interaction term to the control model significantly increases the R^2 at the $p < .05$ level for Subjects 2, 5, 10. This increase is significant at the $p < .01$ level for Subject 7. The addition of the consistency interaction term to the control model also significantly increased the R^2 during this time for Subjects 3, 5, 6 and 9 ($p < .05$).

Using the techniques described in the methods chapter, each of the two regression equations for primacy and consistency was algebraically rearranged for each subject to illustrate the conditional relationship: the regression of Y (resource allocations to the Decline functions during time periods 54-100) on X2 (average industry sales slope) depends upon the values of primacy and consistency when all other variables are held constant. Regression lines were plotted in Figures 3-6 to illustrate relative differences in slope (shown in brackets next to each line) for various values of the primacy interaction term. Figures 7-11 show the plots of the regression lines for various values of the consistency interaction term.

In order to make the analysis of the relationship between the Decline allocation ratio and the industry average slope under varying conditions of primacy and consistency clearer, the slopes for the two conditions of primacy and the three conditions of consistency as well as the T-values for the interaction terms are presented in Tables 11 and 12. In order to cover the range of the residual industry sales slope values, the three points on the X-axis were the mean and four standard deviations above and below the mean.

Examining the Primacy Interaction Effect

The results of the primacy interaction effect analysis for each subject are reported in Table 11 below. The primacy interaction effect is examined only for the Decline allocation ratio since the interaction term had a significant effect for subjects only for this dependent variable. Figures 3 to 6 present the graphs of the results for those subjects with significant interaction effects.

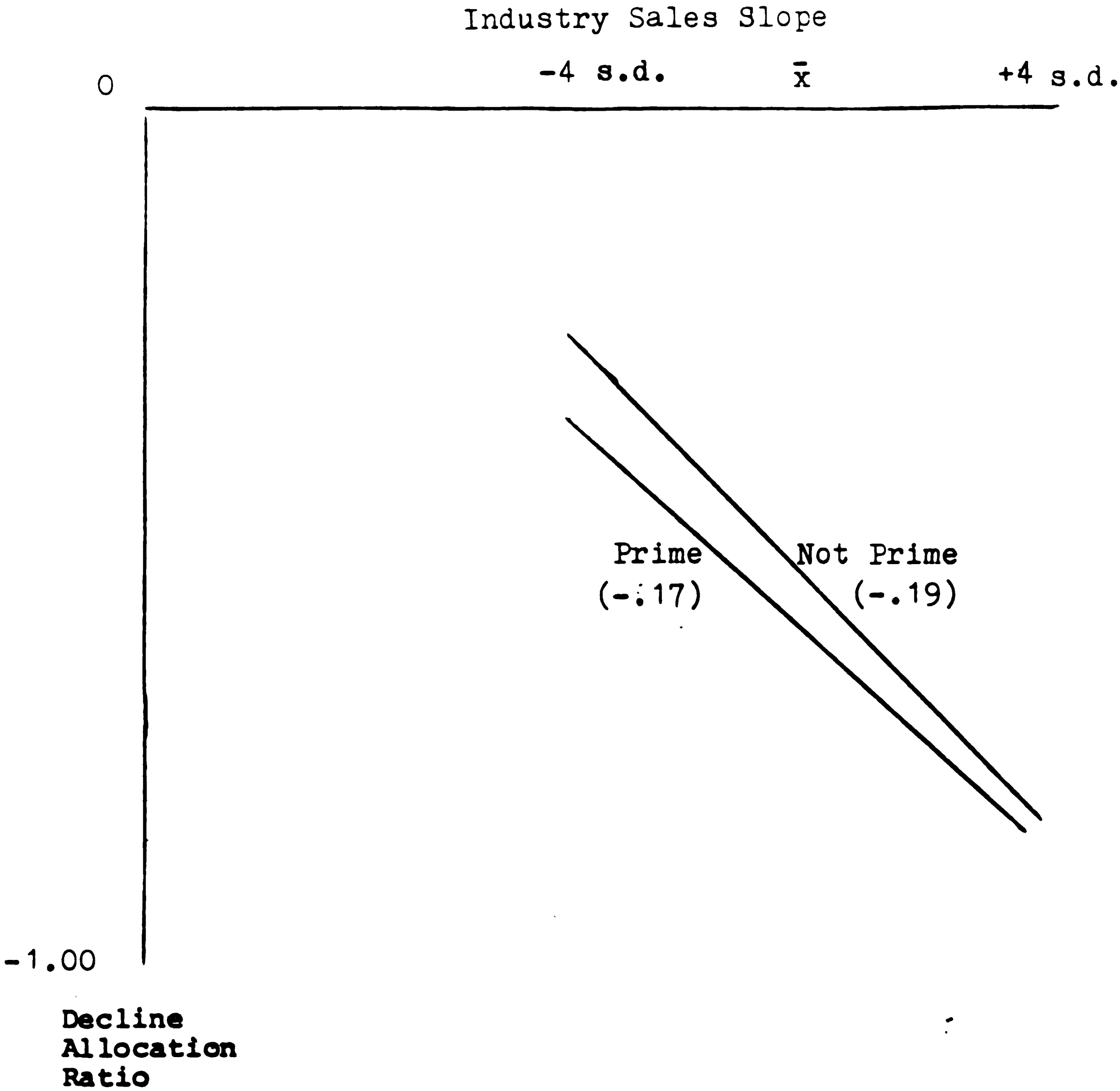

Figure 3

THE RELATIONSHIP BETWEEN INDUSTRY SALES SLOPE AND THE DECLINE ALLOCATION RATIO UNDER CONDITIONS OF PRIMACY FOR SUBJECT 2

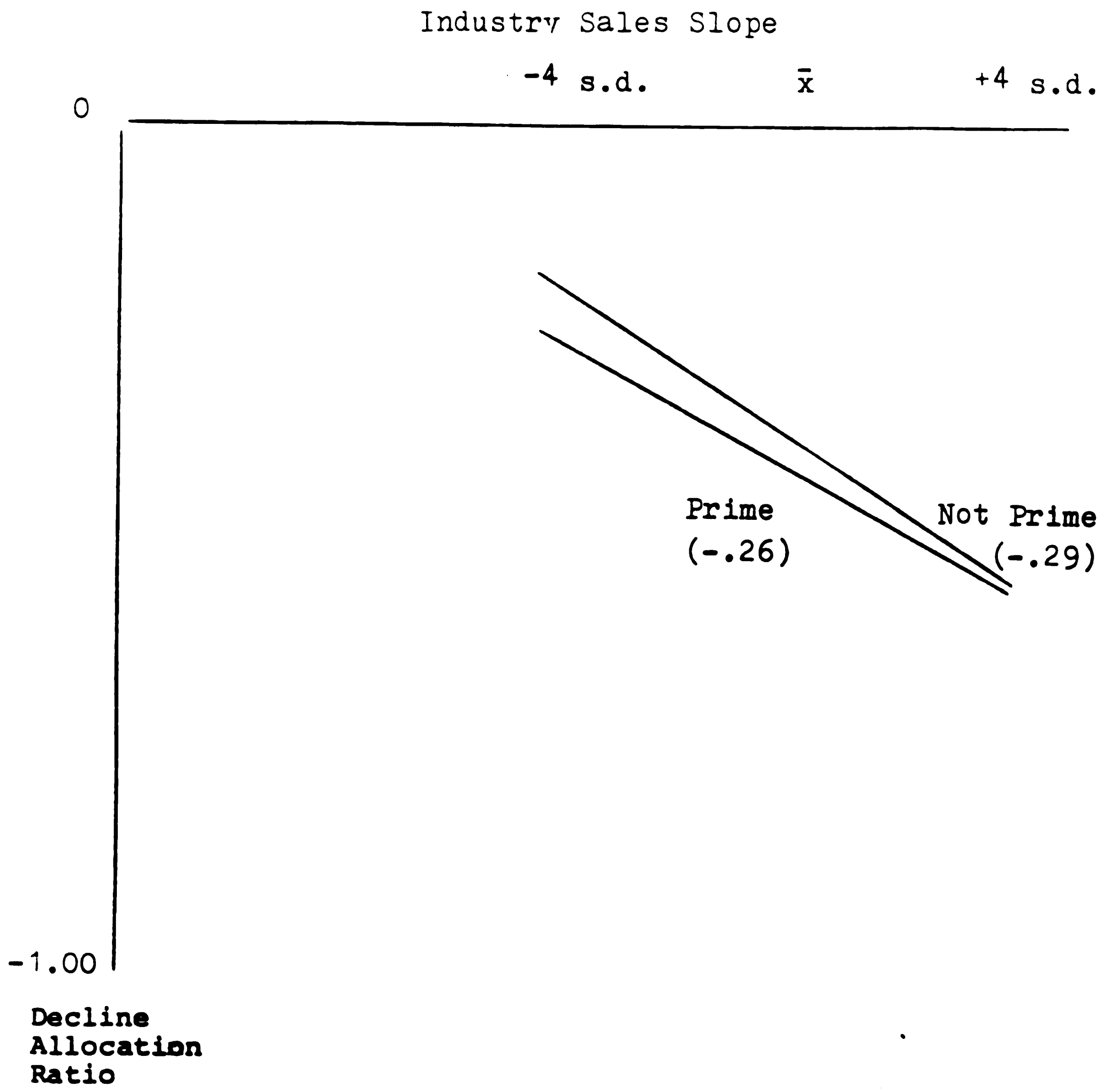

Figure 4

THE RELATIONSHIP BETWEEN INDUSTRY SALES SLOPE AND THE DECLINE ALLOCATION RATIO UNDER CONDITIONS OF PRIMACY FOR SUBJECT 5

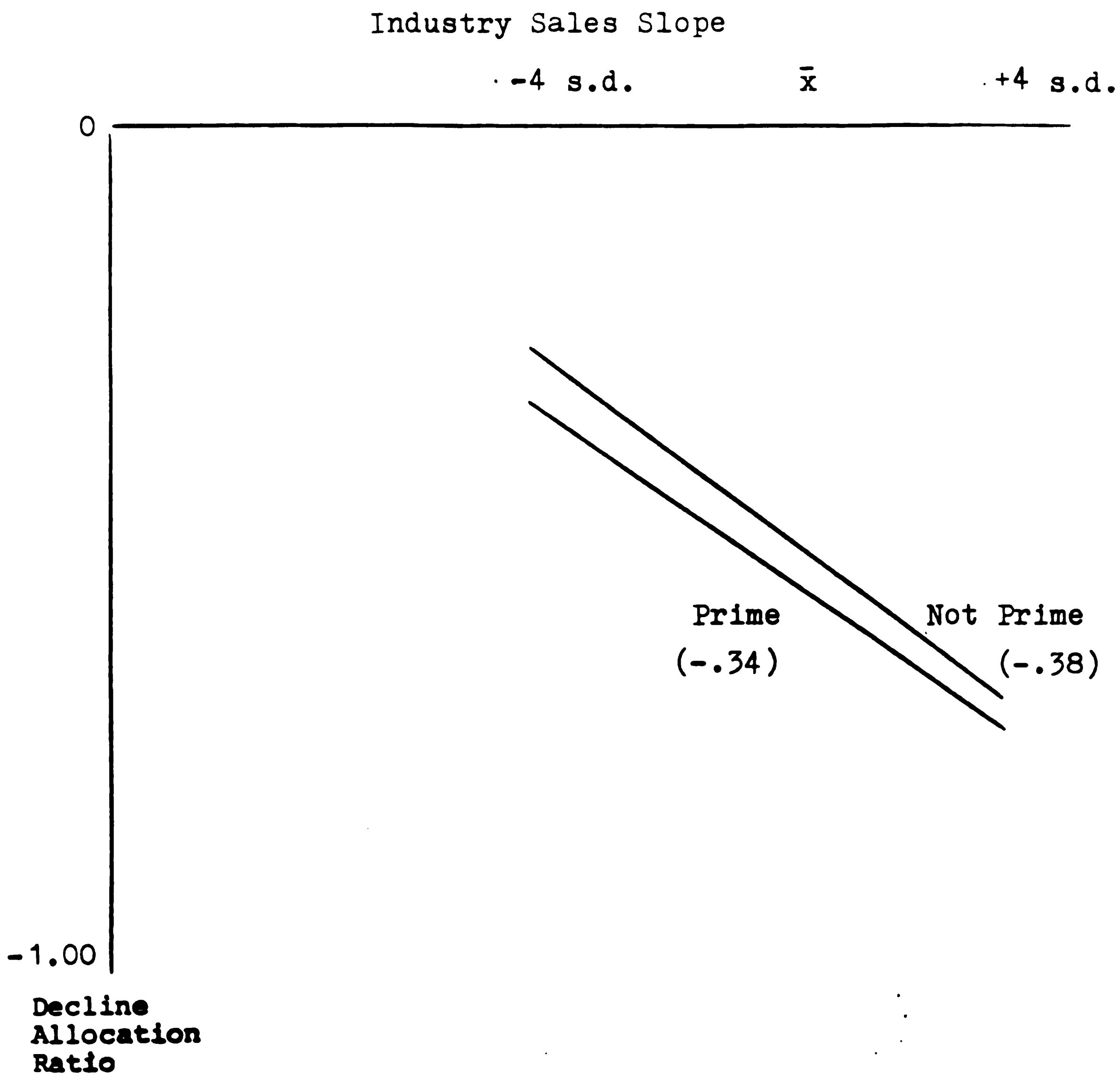

Figure 5

THE RELATIONSHIP BETWEEN INDUSTRY SALES SLOPE AND THE DECLINE ALLOCATION RATIO UNDER CONDITIONS OF PRIMACY FOR SUBJECT 7

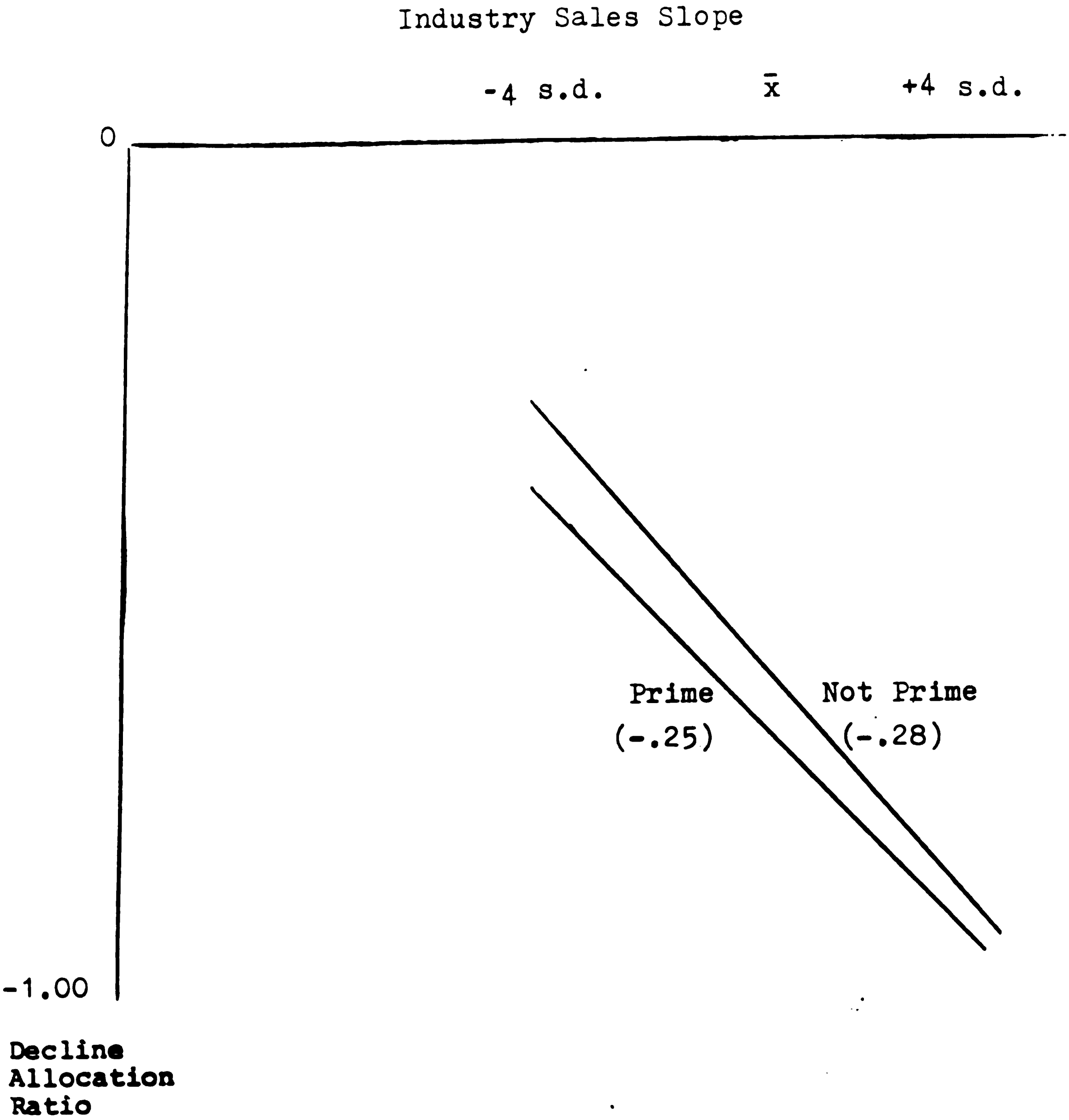

Figure 6

THE RELATIONSHIP BETWEEN INDUSTRY SALES SLOPE AND THE DECLINE ALLOCATION RATIO UNDER CONDITIONS OF PRIMACY FOR SUBJECT 10

Table 11
The Slopes for the Regression of Decline Allocation Ratios on Industry Average Sales Slope Under Conditions of Primacy

Subject	Slope when P=1	Slope when P=0	T-value
1	-.10	-.11	.3972
2	-.17	-.19	.0572
3	-.14	-.15	.3129
4	-.04	-.05	.8212
5	-.26	-.29	.0560
6	-.10	-.11	.1333
7	-.34	-.38	.0006
8	-.02	-.02	.9843
9	-.22	-.24	.2914
10	-.25	-.28	.0645

As stated in Chapter Two, there are two types of interactions: ordinal or disordinal (Pedhauzer, 1982). From the Figures 3 through 6 it is possible to see that there is an ordinal primacy interaction effect for subjects 2, 5, 7 and 10. The differential effect of the industry sales slope when P1=0 does decrease as values of the industry sales slope increase. This is particularly evident for Subjects 2, 5, 7, and 10. The point at which the two lines cross was computed for each of the subjects using the Cohen and Cohen (1983) formula described in the previous chapter. These computations found that the points of crossing for the two lines lie outside the range of interest for all the subjects.

The graphs of the interaction effects reveal a negative relationship between changes in the industry sales slope and the Decline allocation ratio. This is in the hypothesized direction.

The conditional effect of the primacy interaction, however, is opposite of the hypothesized effect. For all subjects, except 8, the slope of the line representing the relationship between changes in the industry sales slope and resource allocation decisions becomes flatter (i.e., less negative) under conditions of primacy. The slope of this line is steeper when the industry average sales curve is not presented first. This does not support Hypothesis 2a which proposed that the relationship between change in allocations and change in the slope of the industry average sales curve would increase when the industry average sales curve was presented first as opposed to any other position.

Examining the Consistency Interaction Effect

To illustrate the conditional effect of the consistency variable on the regression of the Decline allocation ratio on the industry average slope, the regression lines in Figures 7-11 were plotted for high (1 standard deviation above the mean), medium (the mean) and low (1 standard deviation below the mean) consistency values.

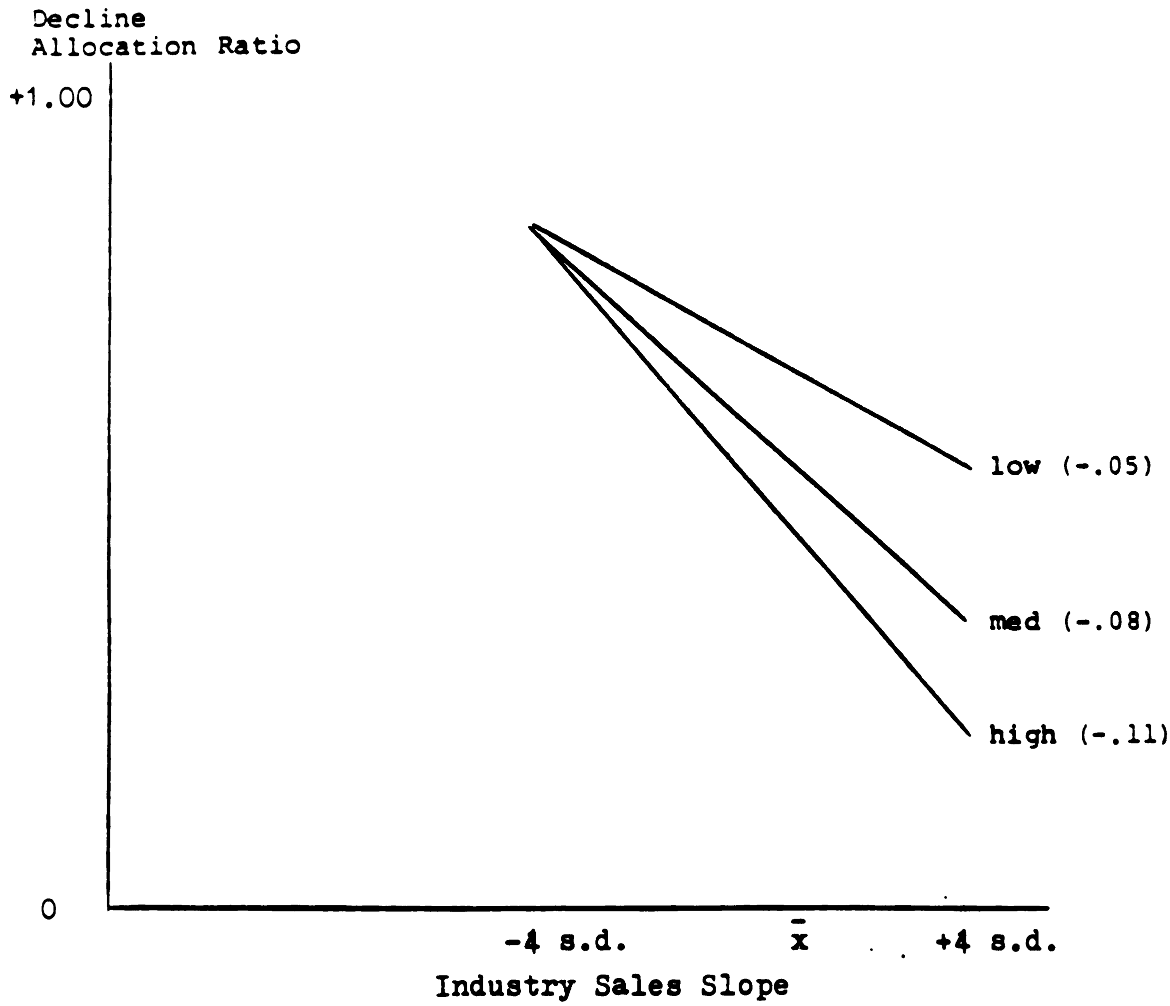

Figure 7

THE RELATIONSHIP BETWEEN INDUSTRY SALES SLOPE AND THE DECLINE ALLOCATION RATIO UNDER CONDITIONS OF CONSISTENCY FOR SUBJECT 3

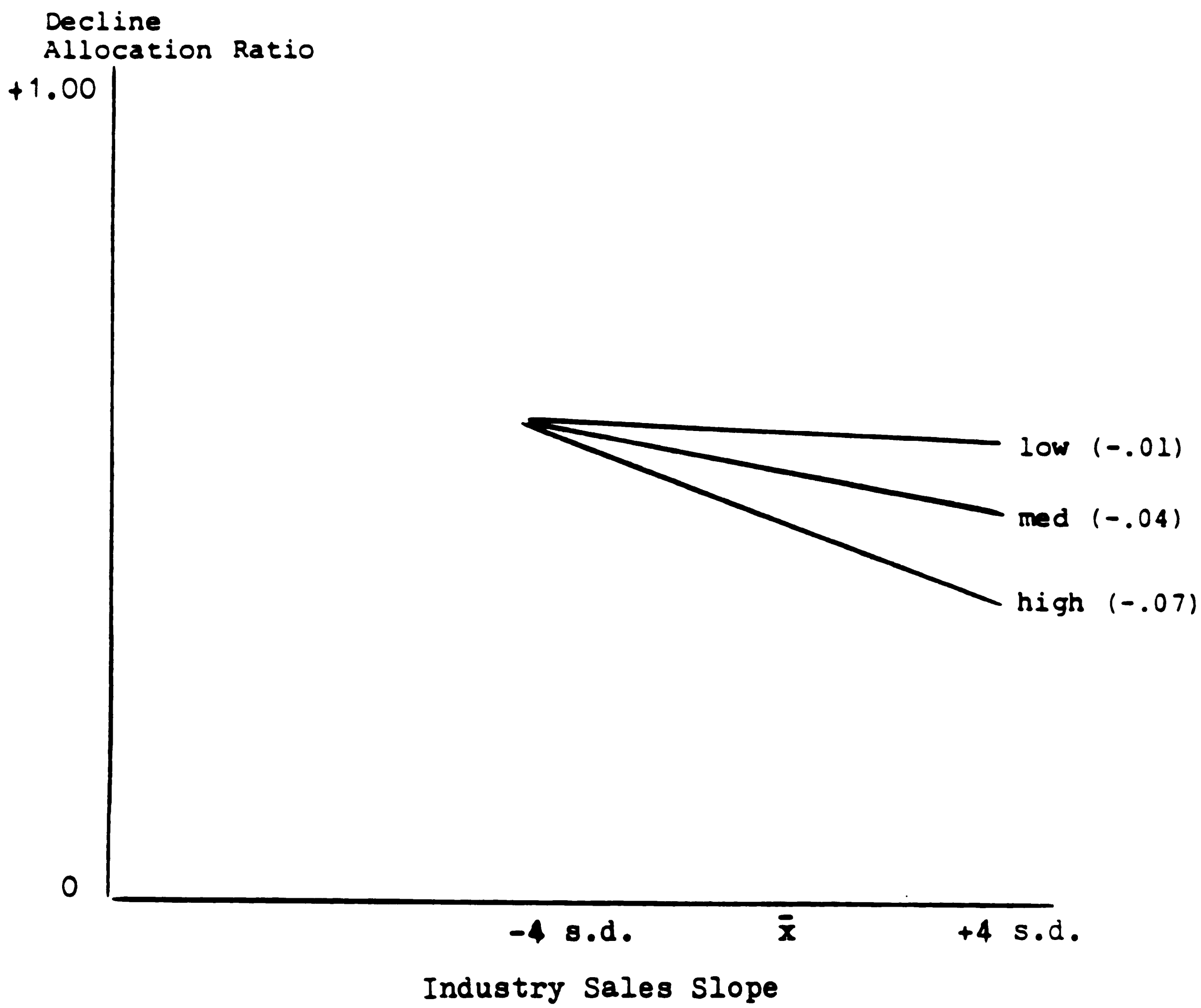

Figure 8

THE RELATIONSHIP BETWEEN INDUSTRY SALES SLOPE AND THE DECLINE ALLOCATION RATIO UNDER CONDITIONS OF CONSISTENCY FOR SUBJECT 5

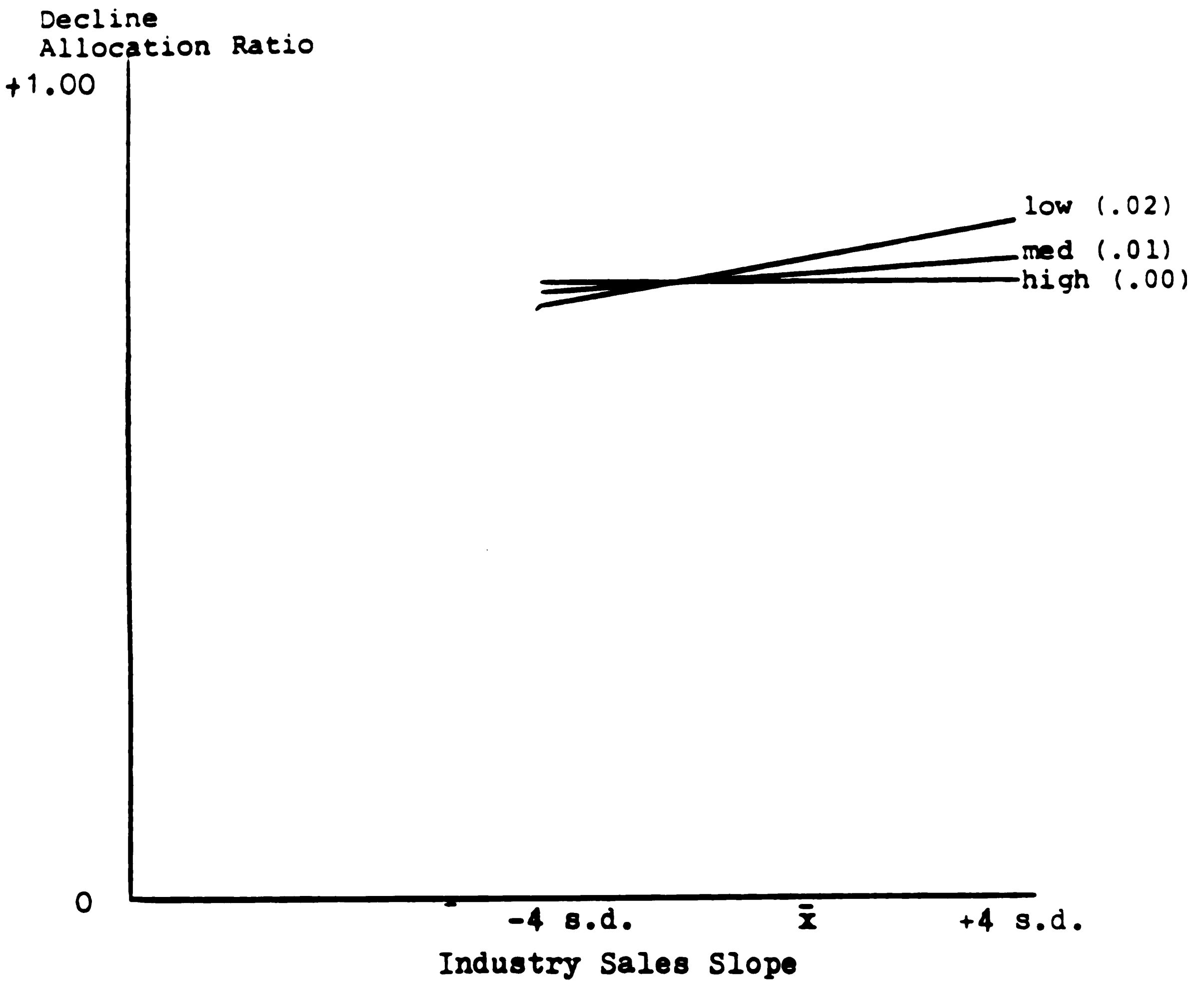

Figure 9

THE RELATIONSHIP BETWEEN INDUSTRY SALES SLOPE AND THE DECLINE ALLOCATION RATIO UNDER CONDITIONS OF CONSISTENCY FOR SUBJECT 6

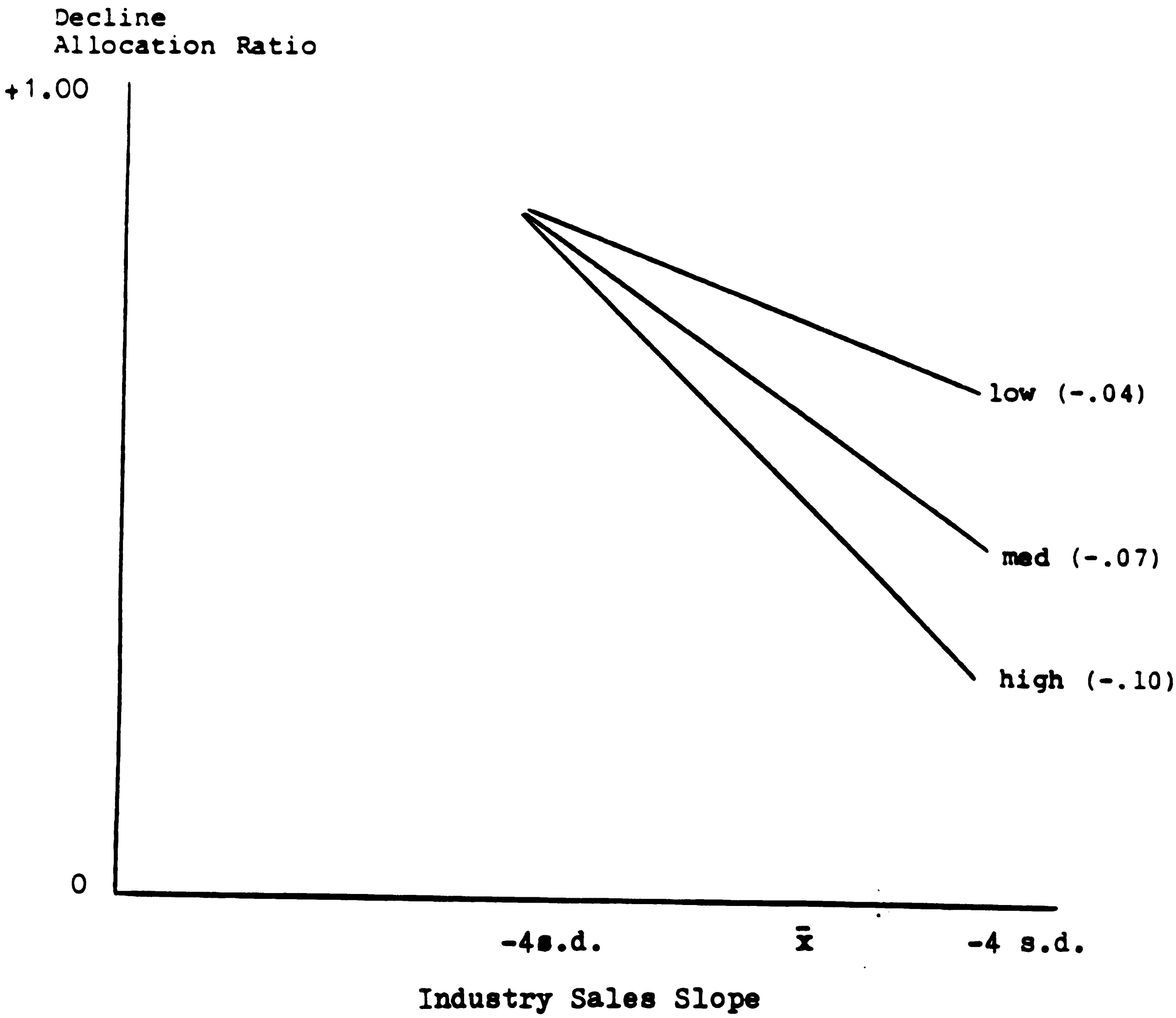

Figure 10

THE RELATIONSHIP BETWEEN INDUSTRY SALES SLOPE AND THE DECLINE ALLOCATION RATIO UNDER CONDITIONS OF CONSISTENCY FOR SUBJECT 8

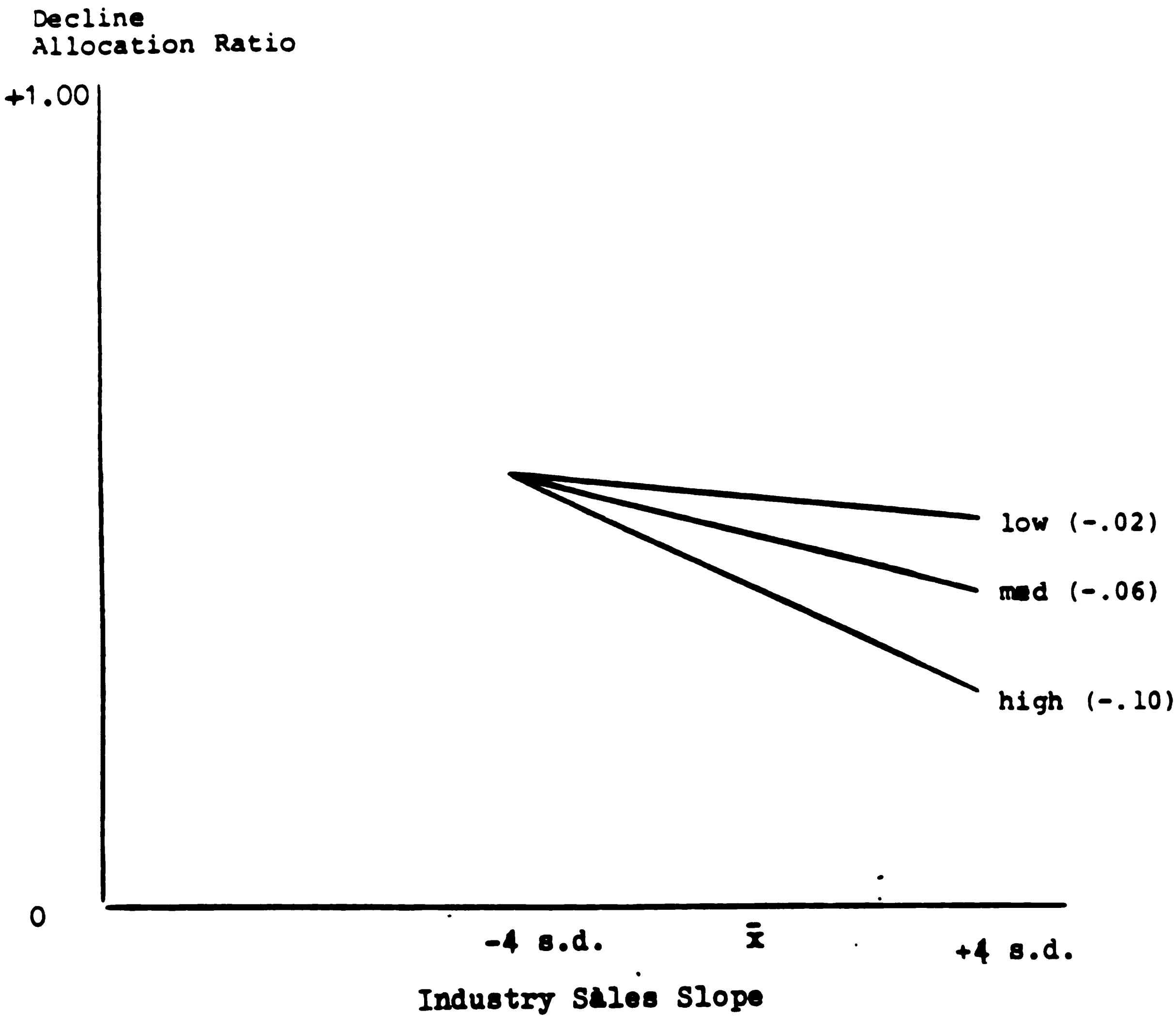

Figure 11

THE RELATIONSHIP BETWEEN INDUSTRY SALES SLOPE AND THE DECLINE ALLOCATION RATIO UNDER CONDITIONS OF CONSISTENCY FOR SUBJECT 9

Table 12
The Slopes for the Regression of Decline Allocation Ratios on Industry Average Sales Slope Under Conditions of Consistency

Subject	Slope when C is High	Slope When C is Medium	Slope When C is Low	T-Value
1	.03	.03	.03	.8407
2	-.01	.00	.01	.1768
3	-.11	-.08	-.05	.0240
4	.03	.02	.01	.6874
5	-.07	-.04	-.01	.0259
6	.00	.01	.02	.0586
7	-.02	-.01	.00	.3426
8	-.10	-.07	-.04	.0770
9	-.10	-.06	-.02	.0428
10	-.08	-.06	-.04	.2268

An examination of Figures 7 through 11 and of the values presented in Table 12 reveals that, for Subject 6, the consistency interaction is a crossed or disordinal one. Again, the points of crossing were computed for the remaining subjects to determine what type of interaction effects were occurring. The results show ordinal consistency interaction effects for Subjects 3, 4, 5, 8, 9 and 10 since the points of crossing for these subjects are not within the range of interest. There are also disordinal consistency interaction effects for Subjects 2 and 7. There is no interaction effect for Subject 1.

The slope for the regression of the Decline allocations ratio on the industry average slope was steeper under conditions of high consistency for Subjects 3, 4, 5, 7, 8, 9, and 10. For these same subjects, the slope was steeper under conditions of medium consistency than it was under conditions of low consistency. Only Subject 6 had the opposite effect for the consistency information processing rule. For this subject, the effect of the slope was greater under conditions of low consistency than under conditions of high consistency. The findings for Subjects 3, 5, 7, 8, 9, and 10 provide some support for Hypothesis 2d which posited that changes in allocations were more likely to occur to the extent that changes in the industry average slope were more consistent in indicating the need to make that change.

Summary

The regression analysis found no support for Hypothesis One. There was mixed support for Hypothesis Two. Significant changes in R^2 were found for both the primacy and the consistency information processing cues for some of the subjects.

The effect of the primacy interaction was opposite of that predicted in Hypothesis 2a. The slope of the regression line was steeper when the industry average sales curve was not presented first. The effect of the consistency interaction was as predicted in Hypothesis 2d. The data showed a trend for the slope of the regression line to get steeper as consistency increased for those subjects were consistency had a significant interaction effect.

CHAPTER FOUR

DISCUSSION AND SUGGESTIONS FOR FUTURE RESEARCH

This chapter focuses on a discussion of the implications of this study's results. Possible explanations for the unconfirmed hypotheses are raised. Based on these explanations, suggestions for future research directions are offered.

Discussion

Hypothesis One

The first hypothesis dealt with the impact of changes in the state variable on individuals' propensity to redefine the problem they are facing. Specifically, Hypothesis One was drawn from the cybernetic decision making literature. According to this literature, decision makers redefine the decision situations they face when they observe a change in the characteristics of state variables (Ashby, 1952). For the current research situation, it was expected that, at a given time period, decision makers would change their resource allocations to functions associated with a given PMM stage when the slope of the industry sales curve indicated a need for such a change. Overall, the data gathered for this research do not support this hypothesis.

There are several possible explanations for these results. First, cognitive psychologists have suggested that people are gross processors of information (Markus & Zajonc, 1985; Ebbesen, 1980). People tend to overutilize simplistic or intuitive inferential strategies especially when they are faced with ambiguous information (Barnes, 1984; Nisbett & Ross, 1980; Payne, 1976). Markus and Zajonc (1985) note that people also tend to use more simplified cognitive structures when there is too much information in the environment. When faced with an information-rich environment, people must be selective about the information that is processed (Weick, 1979; March, 1945). The brain allows humans to eliminate whole sets of possibilities in a decision making situation without conscious consideration (Beer, 1964; Stohl and Redding, 1987).

Beer (1964) proposes that the human brain does not comprehend complex patterns presented instantaneously to it (Beer, 1964). Rather, the complex pattern is fully comprehended only when it is spread out in time (Beer, 1964). Since subjects were taught a PMM model that encompassed the general spectrum of the three stages without any specific focus on individual decisions at each time period, it is possible that subjects were unable to respond to a change in slope at a given time period because that specific change was not interpretable in and of itself. Instead, people need to place information within a schema in order to interpret that information usefully (Markus and Zajonc, 1985).

Head (1920) contends that a schema is a type of continuous standard that permits an integration of what is currently occurring with what went on before. Beer (1964) suggests that, for the brain, the problem of incompleteness in a pattern of information is overcome by a network capable of comparing the incomplete pattern with complete ones. Hastie (1981) notes that people try to comprehend informational items by retrieving additional data from long term memory until the item is understood. People learn by weighing information within a historical frame of reference (Beer, 1964).

Computer simulations, such as the one used here, may be successfully programmed to reconstruct the rich environment decision makers face in the business world (Wexley and Latham, 1981). The richness of the information generated by the computer about the simulated PMM model may have led the subjects to ignore the information about the specific changes in the industry slope at each time period when making their resource allocation changes. The information screening process may have made subjects less sensitive to small changes in the slope of the industry sales curve, thus protecting themselves from information overload. This process makes it unnecessary for the subjects to learn the pattern of trivial "noise" in the environment (Beer, 1964). In the current situation, the small changes in the slope of the industry sales curve at each time period also may not have fit subjects' broad, general schemata of a particular PMM stage. Therefore, this information may have been considered to be "noise" and so was not used by subjects in their resource allocation decisions.

One of the reasons subjects may have considered the changes in slope at each individual time period to be noise is that they found this information to be routine and, therefore, did not utilize it in their decision making process. Routine information may become redundant over time, and redundant information is often not used in decision making. As Ilgen, Fisher and Taylor (1979) conclude, based on their literature review, feedback information should provide the subject with more knowledge about the situation than s/he currently has available. Only then will this information be attended to and, subsequently, be used. This thesis would lead to the contention that subjects in the present investigation may not have considered changes in the slope at each decision time period when making their resource allocation decisions. The change information may have become so routine that it was outweighed by other information considered to be more relevant to the broader schema of the PMM stage.

The preceding theoretical discussion leads to the proposition that when subjects made an assessment of the validity of their problem definition they may have used the information about the industry sales curve that they had gained over time rather than just confining their information base to the change in the slope at one time period. Based on this alternative theoretical hypothesis, post-hoc analyses were done on the data.

A moving average was computed for the average industry sales slope value over the five previous time periods. For this moving average, each time period was weighted equally. The Introduction allocation ratio was regressed on the moving average of the industry sales slope for the first set of decision periods. The Decline allocation ratio was regressed on this moving average for the second set of decision periods for each subject. The results are reported in Tables 13 and 14.

TABLE 13

SUMMARY OF REGRESSION ANALYSIS OF THE MOVING AVERAGE MODEL
(Time Periods 7-53)

Introduction Expenses			
S	R^2	F	P
1	.15	8.16	.007
2	.17	9.25	.004
3	.17	9.41	.004
4	.24	14.12	.0005
5	.26	15.78	.0003
6	.09	4.25	.05
7	.23	13.71	.0006
8	.15	8.17	.006
9	.21	11.85	.001
10	.14	7.21	.01

The analyses revealed significant relationships for all 10 subjects for the Introduction resource allocation ratio for the first set of decision times. It appears that the subjects were using the information provided by a moving average of the average industry sales curve when making their resource allocations to the Introduction functions.

TABLE 14

SUMMARY OF REGRESSION ANALYSIS OF THE MOVING AVERAGE MODEL
(Time Periods 54-100)

Decline Expenses			
S	R^2	F	P
1	.05	2.15	.15
2	.26	15.49	.0003
3	.15	8.07	.007
4	.36	25.49	.0001
5	.18	9.57	.003
6	.04	2.05	.16
7	.11	5.41	.02
8	.02	1.14	.29
9	.18	10.00	.003
10	.15	8.15	.007

For the second set of time periods, the analyses revealed that seven subjects had significant relationships between the Decline resource allocation ratio and the moving average of the industry sales slope.

These results provide some evidence for the validity of the data, per se, as well as some empirical support for the post-hoc hypothesis. Specifically, these results indicate that the change in slope at each decision time period may not have been the characteristic of the state variable that subjects assessed to make their problem redefinition decisions.

The post-hoc findings suggest that decision makers used their knowledge of what had happened to the industry average sales curve in previous time periods to understand the current change. These findings do not contradict the original model of problem redefinition proposed in Chapter One. Rather, these findings extend that model. The findings provide more information about the type of characteristics of the state variable decision makers assess to make a problem redefinition decision.

HYPOTHESIS TWO

The literature review presented in Chapter One suggested that information processing variables may be related to a decision maker's decision to implement problem redefinition. Literature from a number of areas, including information processing, heuristics and attribution theory, provided four theoretically based information processing variables. Hypothesis Two suggested that decision makers implementation of problem redefinition may be related to the order in which that information was presented, to the information's visual vividness and to the consistency of the information across time. The results of the current study provide mixed support for Hypothesis Two.

There was not a significant increase in R^2 for any of the interaction terms for any of the subjects for their Introduction resource allocation decisions during the first set of decision iterations. For time periods 54-100, some subjects appeared to use the information processing cues in making their resource allocation decisions. The two cues that had significant effects for some of the subjects were the primacy and the consistency cues. Subjects 2, 5, 7 and 10 showed significant relationships for primacy for the Decline allocations. Subjects 3, 5, 6, and 9 appeared to pay attention to the consistency cue when making their Decline allocations.

Information processing cues were used by some of the subjects only during the latter time periods of the PMM cycle. Literature from communication research would suggest that subjects may have been faced with "message ambiguity" during the first set of decision iterations. In other words, when the subjects first engaged in the simulation, they may have been unable to select, from their previous experience, a single interpretation of the information they were presented. The confusion may have resulted from an inability to construct any plausible interpretation whatever of that information (Stohl and Redding, 1987).

One of the reasons for subjects' initial confusion may have been that the first half of the simulation had several unexpected decreases and increases in industry average sales. This is in accordance with the PMM literature which notes that the product market may go through a number of temporary Decline or Growth phases during the course of the life cycle of the product (Porter, 1980). Although the subjects were informed of this possibility during the PMM training exercise, observation, anecdotal evidence and subject reactions during the debriefing session revealed that most students were confused by the sudden and severe increases and decreases in the market during the first half of the simulation. This confusion may have manifested itself in subjects' uncertainty about which PMM stage they were in during the initial set of decisions.

It is also possible that subjects learned how to do the simulation over time. This learning may have decreased their confusion about the simulation. A study by Moch, Malik and Berge (1988), using a sample of subjects who did the exact same simulation used for this research, found that learning did take place over the course of the simulation. Subjects' post-test scores on a PMM knowledge test were significantly higher than their pre-test scores.

This learning may have contributed to the subsequent decrease in confusion and in the increased integration of the information processing rules in their decision making processes by subjects. Beer (1964) argues that as people build up experience with the uncertainties with which they deal in a given situation, they become more sure of themselves. Experience in a given situation may decrease the equivocality in the situation. A reduction in equivocality is likely to lead the subjects to use more complex information processing rules or schemata when trying to understand the situation (Weick, 1979).

Higgins and Bargh (1988) propose that, in certain situations, people create new schemata while they are learning about a new situation. Subjects may have taken the first half of the simulation to develop schemata about how to use the information processing cues in their decision making process. They may have then applied these schemata in the latter half of the simulation.

Primacy

Hypothesis 2a proposed that decision makers are more likely to undertake problem redefinition when the the state variable indicating the need for such a change appears first in a sequence of information. The primacy interaction term had a significant conditional effect on the relationship between changes in industry average sales slope and allocations to Decline functions for three subjects ($p < .05$) and it approached significance for one subject ($p < .06$).

The direction of this relationship was unexpected. Specifically, industry average slope had more impact on the Decline allocation ratio when the industry average curve was not presented first. This trend was true for nine of the subjects. And, it is opposite to Hypothesis 2a.

The fact that subjects were given two qualitatively different types of performance feedback may be central to trying to understand why subjects gave more weight to the slope of the industry average sales when that information did not appear first in the feedback sequence. Research done on human information processing activities offers some plausible theoretical explanations for these results.

The average industry sales data was information about the conditions of the product's market. The industry level data could be labeled as base rate data

(Hogarth, 1980; Tversky and Kahneman, 1974). Specifically, base rate information provides the decision maker with background information on the judgmental situation. It is more abstract information for the decision maker (Hogarth, 1980). In the experiments done by Tversky and Kahneman (1974) the base rate is usually a population level statistic. However, the purpose of that information is the same as that implied in the average industry sales graph presented in this study. The second characteristic of the industry level information was that it could not be manipulated by the action of the subject. The subjects were aware that the industry sales were programmed into the simulation and were not influenced by their companies' performance. Subjects' gross and net incomes were a direct outcome of their resource allocation decisions and, so were more personally relevant. This data contained meaningful information to subjects about their own companies' performance. Nisbett and Ross (1980) label this type of information as "case specific." It is more concrete for the decision makers (Hogarth, 1980).

Tversky and Kahneman (1974) discovered the existence of the base rate bias when conducting several of their information processing studies. The authors found that people are prone to ignore base rate information when making probability judgments. Rather, decision makers are more influenced by case-specific data (Hogarth, 1980;

Nisbett and Ross, 1980; Kahneman and Tversky, 1979; Tversky and Kahneman, 1974). In circumstances where subjects have both case specific data and base rate information, they are more likely to ignore the base rates and make their judgments based almost entirely on the case specific data (Hogarth, 1980; Nisbett and Ross, 1980). Hogarth (1980) states that people will use base rate information under very limited circumstances. According to Hogarth (1980), this type of data is more likely to be used in the absence of case specific information. Base rate information is also more likely to be used when the decision maker sees the base rates as having causal meaning for the situation or when the base rate information makes sense in relation to the case specific information (Hogarth, 1980). As Hogarth (1980) notes, people tend to give more weight to data with causal meaning than to data perceived to be indicative or diagnostic.

The industry average sales information is analogous to the concept of base rate. The company-level performance is more case-specific. The base rate bias suggests that decision makers are not likely to use the base rate information unless they see the link between the base rates and the case-specific feedback. In the current case, subjects gave more weight to the change in industry average sales slope only after seeing some or all of the case-specific feedback: their own gross and net incomes. It is possible that subjects needed to have feedback on their own performance in order to understand the changes in the industry sales slope. Once the subjects had the case-specific information, it may have been easier for them to see the link with the industry level sales that Hogarth (1980) argues is necessary if the base rate information is to be used.

It is argued here that people generally tend to be inductive, not deductive thinkers. In other words, people find it easier to generalize their understanding of a specific situation to the broader context than to draw implications about specific cases from the broader context. Sutherland (1973) notes that inductive reasoning is the prevalent mode of thinking in the physical, natural and social sciences. The base rate bias also illustrates the prevalence of inductive thinking. Here, too, research has shown that people find it easier to draw implications for the broader context from their understanding of specific cases (e.g., Tversky and Kahneman, 1974).

Of course, the figure-ground comparison is also possible when the industry sales curve is presented first. Based on an extensive empirical framework developed by Tversky and Kahneman (1981; 1974), it is possible to argue that this does not always hold. A series of experiments by Tversky and Kahneman (1981) found that decision makers changed their decision choices when the problems presented to them were framed in various manners. Decision frames are the decision makers' conceptions of acts, outcomes and contingencies associated with a particular choice (Tversky and Kahneman, 1981). These researchers found systematic reversals in preferences of decision solutions by varying the framing of the acts, contingencies and outcomes of decision situations. Based on this framework, it could be argued that when the average industry sales curve was presented to the subjects first, the decision makers may have used the industry level feedback for a different purpose than when the base rate information was not presented first. The subjects, during the former feedback sequence, did not have the case-specific information to define the relevant aspects of the abstract base rate information needed for a figure-ground assessment. It is possible that when the industry sales curve was presented first, it was used for purely diagnostic purposes. As Hogarth (1980) notes, base rate information used primarily for a diagnostic purpose is more difficult for subjects to use in their decision making process. As a consequence, the industry level information may not have been weighed as heavily by decision makers in subsequent allocation decisions.

Consistency

Kelley (1967) suggested that people are influenced by the consistency of the information they observe when they make attributions for performance. This concept was adapted to the current decision making situation in Hypothesis 2d to suggest that decision makers are influenced by the degree to which a state variable consistently indicates the need for a change in the problem redefinition. This hypothesis was replicated by the results from Subjects 3, 5, 6, and 9.

The notion of a "norm of consistency" has previously been discussed in organizational behavior (Pfeffer, 1981; Staw, 1976). According to these authors, consistency in action has great social value. In previous literature, the concept of consistency has been operationalized in a variety of ways. Attribution theory research has focused on how the consistency of people's behaviors affects attributions for outcomes (Kelley, 1967). In the social information processing literature, research has investigated the relationship between consistency of people's expectancies of others and their subsequent judgement of those people (Higgins and Bargh, 1988). Staw and his colleagues has studied the impact of the norm of consistency on decision makers' commitment to decision solutions which have failed. Finally, the information processing literature has found support for the impact of the consistency of various data sources on subsequent decisions (Hogarth, 1980; Nisbett and Ross, 1980). All of these different conceptions of consistency have been significantly supported by empirical tests across different situations.

The current research expanded the application of this construct by investigating the impact of the consistency of the feedback information itself on decision makers' resource allocation decisions. The important characteristic of this operationalization is the fact that the impact of the consistency of information over time was assessed. Most decision making studies have not examined this aspect of the consistency information processing rule since the investigations tend to be static. As evident in the strategic management function of environmental scanning, decision makers in field settings gather information on the same variables over time in order to assess whether or not they are on the right track. Cybernetic decision theory proposes much the same process in its contention that decision makers attend to state variable feedback loops. Decision makers, again, are gathering information on the same variables over time. Based on this framework, the investigation of the impact of the consistency of information over time is an important expansion of the consistency information processing rule.

The results from this study suggest that some of the subjects used this information processing rule. The slope of the regression line representing the relationship between changes in the industry average sales slope and the decline allocation ratio was significantly steeper under conditions of greater consistency for Subjects 3, 5, 8 and 9. A similar trend was observed for Subjects 4, 7, and 10 as well although it was not significant. An opposite effect was found only for Subject 6. These results suggest that some decision makers may be more likely to implement problem redefinition when the characteristics of the state variable indicate the need for such a change consistently over time.

Methodological Considerations

The design of this study was atypical of standard decision making research. One of the unique aspects of this research was the longitudinal nature of the decision task. The computer simulation allowed the researchers to compress time through programming techniques. This created a research situation where subjects were forced to make recursive decisions and address the consequences. Future research in decision making should continue to capitalize on the unique advantages of using the computer simulation as a research tool. The results from this study highlight the importance of studying decision making in a dynamic context where decision makers are faced with recurring decisions. In order to achieve greater ecological validity, decision making research should create decision situations that occur over time and are embedded within an external environment with which the decision situations interact.

One of the ways to increase this ecological validity and meet the necessary conditions stated above is to use computer simulations of real-world business situations. The computer simulation used for this study underscores the usefulness of this procedure. As evident by the various results reported earlier, the simulation was able to recreate real-world environmental uncertainty for the subjects. In addition, the computer simulation enabled the creation of a dynamic decision situation. The computer simulation gave the subjects immediate feedback regarding their decision choices. Closely simulating a realistic business situation, subjects were forced to make their own interpretations of performance feedback in order to proceed with the next set of resource allocation decisions. Subjects had to face the consequences of their decisions and their outcomes were made meaningful to them since they were graded on their performance in the simulation. The research level of control was high while the context of the experiment was characterized by a high level of complexity.

The major methodological concern about the current research design is a function of the time series nature of the data. Specifically, time series data is characterized by autocorrelation (Neter, Wasserman and Kutner, 1985). In time series data, the error terms are correlated positively over time. This positive correlation of error terms leads to a number of problems with multiple regression. In an effort to eliminate the threat to the multiple regression analyses associated with autocorrelation, a number of radical adjustments were made on both the independent and dependent variables. As discussed in the statistical analysis section, the industry sales variable was regressed on time and the residual was used to form the independent variable actually used for the analyses. For the dependent variables, the resource allocations were regressed on the predicted industry slope value for the same reason. This radical adjustment may have increased the possibility of Type II error occurring since the adjustments for autocorrelation may have also eliminated some meaningful variance.

Some people may argue that standard regression analysis is an inappropriate statistical technique to use for the analysis of time series data (McCleary and Hay, 1980; McCain and McCleary, 1979). Rather, many econometric texts suggest the use of time series analysis techniques (Neter et al, 1985). The Box-Jenkins approach to time series analysis was considered as an option for this research. However, time series analysis is not capable of handling both independent and dependent time series with interaction terms. Time series techniques are currently at a stage of development where each one of these analyses must be done separately. This was inappropriate for the theoretical purposes of this investigation. Every attempt was made to try to eliminate the problems associated with regression analysis of time series data when the statistical analysis was designed and implemented.

Conclusions

Problem Redefinition Issues

The focus of interest in this research has been the problem redefinition stage of the decision making process. In Chapter One, four of the principle models of decision making were reviewed and their approaches to problem redefinition were outlined.

The rational and satisficing models of decision making essentially did not address the problem redefinition issue. The incremental model proposed that a series of incremental changes resulting from changes in the choice of decision alternatives would eventually lead to problem redefinition. The incremental problem redefinition is an outcome of incremental changes decision makers make within their current definition of the problem. The incremental model's conception of problem redefinition implies that decision makers attend to only one feedback loop when making decisions. This feedback loop is concerned with the satisfactoriness of the outcomes generated by the decision solution that is currently implemented. Unsatisfactory outcomes will lead to changes in the choice of the decision alternatives. These changes may eventually lead to problem redefinition (Quinn, 1980). This is incremental problem redefinition identified by the decision making models.

One major limitation of the incremental model is that it does not explain those situations where problem redefinition is a distinct or quantum change from the current decision definition. As was pointed out in Chapter One, a distinct or quantum change in a decision definition may be likely to occur in a dynamic decision situation.

The cybernetic model of decision making provides a theoretical framework that addresses this issue. Based on cybernetic principles of decision making, it was proposed that decision makers attend to two feedback loops (Ashby, 1952). The first feedback loop is used to assess the validity of decision makers' performance by monitoring critical performance variables. This feedback loop is also included in the incremental model. The second feedback loop is used to assess the validity of the way decision makers have defined the problem situation through the examination of state variables (Ashby, 1952). Numerous studies have presented both theoretical and empirical arguments contending that decision making is dynamic, generating a change in the decision situation over time (Mausch, 1985; Nystrom and Starbuck, 1984). This change in the decision situation requires a corresponding change in the problem definition. Unlike the incremental model, the cybernetic paradigm does not propose that a series of changes based on the first feedback loop will lead to any type of problem redefinition. According to cybernetic theory, changes in the characteristics of the state variables should lead to a change in the definition of the problem by decision makers. This is the second type of problem redefinition identified by previous decision making models: a conscious change in the definition of the problem.

The current investigation operationalized the cybernetic problem redefinition concept by creating a ratio of the amount allocated to organizational functions associated with a stage of the PMM (Introduction or

Decline) to the total amount of money allocated to all organizational functions. The regressions of these two ratios on the industry average sales slope allowed inferences to be made about subjects' problem redefinition decisions since regression analysis defines the relationships between the independent and dependent variables. Specifically, the regression analyses provided data about the effect of one unit change in the independent variable, the industry sales slope, on changes in the dependent variable, resource allocations to either the Introduction or Decline organizational functions relative to total resource allocations. This was defined as problem redefinition for this investigation.

The results of the regression of the two ratios on the industry average sales slope were nonsignificant for all subjects for both sets of time periods. This raised questions about what information the subjects used to make their problem redefinition decisions. Observations of the subjects during the simulation phase of the investigation confirmed that subjects were looking at the state variable for these decisions but this effect was not captured by the regression analysis. For this reason, as discussed earlier, the two dependent variables were regressed on the moving average of the industry sales slope. The significant results of these analyses supported the observations that most of the subjects were using the state variable to assess the validity of their problem definitions.

This evidence generated the post hoc hypothesis that the operationalization of the problem redefinition may have been capturing more of the subjects' decision processes than originally anticipated. All evidence to this point indicates that subjects seem to have used a different approach to problem redefinition than that proposed by either the cybernetic or the incremental model. This data suggests that subjects may have been making incremental adjustments to their problem redefinitions over time. This is a third type of problem redefinition, theoretically different from both the incremental and the cybernetic conceptions of problem redefinition.

To illustrate this hypothesis, the Introduction and Decline ratios, unadjusted for autocorrelation, were plotted against time for all the subjects. Some of these plots are presented in Figures 12-17 for illustration purposes. An examination of these plots reveals that subjects appear to make incremental adjustments to their patterns of resource allocations. It is important to keep in mind that the patterns of resource allocations, for this research, represent decision makers' definitions of the problem.

```
             Plot of INT*T1
INT
1.0 +
0.9 +
0.8 +
0.7 +           AA AAA A
0.6 +                   A AAA AA AA
0.5 +                              A AA AAA
0.4 +                                      AA
0.3 +                                         AAA
0.2 +                                             AA AAA AA AAA AA AAA AA
0.1 +
0.0 +
    --+------+------+------+------+------+------+------+------+------+-----
      0      5      10     15     20     25     30     35     40     45

                                  T1
```

Figure 12

GRAPH OF INTRODUCTION ALLOCATION RATIO OVER TIME
FOR SUBJECT 2
(Time Periods 7-53)

```
            Plot of INT*T1
INT
1.0 +
0.9 +
0.8 +
0.7 +
0.6 +          AA AAA AA A A A
0.5 +                    A   A AAA
0.4 +                              AA
0.3 +                                 AAA AA AAA AA
0.2 +                                               AAA AA AAA AA AAA AA
0.1 +
0.0 +
    --+------+------+------+------+------+------+------+------+------+-----
      0      5     10     15     20     25     30     35     40     45

                                T1
```

Figure 13

GRAPH OF INTRODUCTION ALLOCATION RATIO OVER TIME
FOR SUBJECT 4
(Time Periods 7-53)

```
             Plot of INT*T1
INT
1.0 +
0.9 +
0.8 +
0.7 +
0.6 +           AA AAA AA
0.5 +                     AAA AA A
0.4 +                             AA
0.3 +                                AA AAA AA AAA
0.2 +                                              AA AAA AA AAA AA AAA AA
0.1 +
0.0 +
    --+------+------+------+------+------+------+------+------+------+-----
      0      5     10     15     20     25     30     35     40     45

                                      T1
```

Figure 14

**GRAPH OF INTRODUCTION ALLOCATION RATIO OVER TIME
FOR SUBJECT 10
(Time Periods 7-53)**

```
                     Plot of DEC*T1
DEC
1.0 +
0.9 +
0.8 +                                          AA  A                 AA A
0.7 +                                    A  AA   A  A AAA  A AAA AA A    A
0.6 +       AAA AA AAA AA AAA AA AAA AA A A               A
0.5 +
0.4 +
0.3 +
0.2 +
0.1 +
0.0 +
    --+------+------+------+------+------+------+------+------+------+-----
     50     55     60     65     70     75     80     85     90     95

                                      T1
```

Figure 15

GRAPH OF DECLINE ALLOCATION RATIO OVER TIME FOR SUBJECT 3 (Time Periods 54-100)

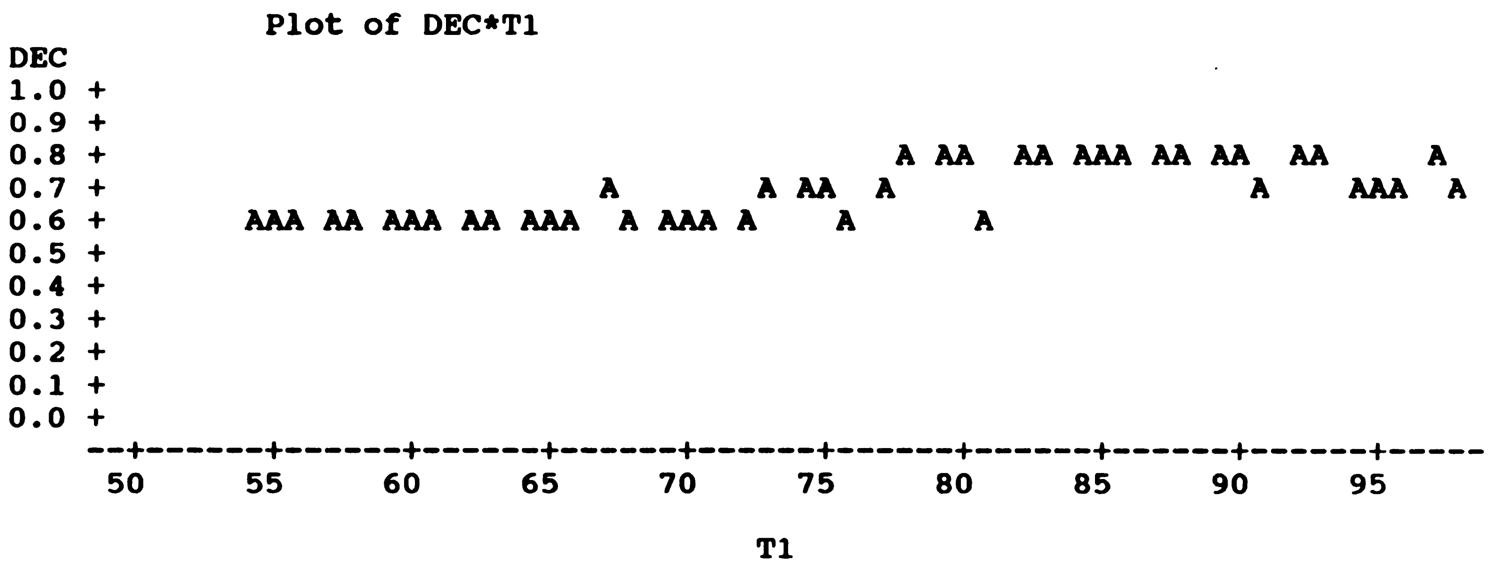

Figure 16

GRAPH OF DECLINE ALLOCATION RATIO OVER TIME
FOR SUBJECT 5
(Time Periods 54-100)

```
          Plot of DEC*T1
DEC
1.0 +
0.9 +                                             A                 AA A
0.8 +                                              AA AA AAA AA AAA     AA AA
0.7 +                                          A   AA
0.6 +        AAA AA AAA AA AAA AA AAA AA A A
0.5 +
0.4 +
0.3 +
0.2 +
0.1 +
0.0 +
    --+------+------+------+------+------+------+------+------+------+-----
      50     55     60     65     70     75     80     85     90     95

                                   T1
```

Figure 17

GRAPH OF DECLINE ALLOCATION RATIO OVER TIME
FOR SUBJECT 9
(Time Periods 54-100)

The adjustment of the pattern of resource allocations is very obvious in Figures 12 through 14. There is a clear pattern of an incremental reduction in Introduction allocation expenses over time. At first glance, the pattern of incremental change in problem redefinition is not as clear in Figures 15 through 17. However, the pattern does exist. For all three subjects, there is an incremental increase in the Decline resource allocation ratio which begins around the 75th time period. There appear to be several time periods of incremental adjustments in the patterns of resource allocations for the subjects before the allocations to the Decline functions generally level off. The patterns evident in Figures 12 to 17 are generally replicated across the remaining subjects. These plots provide tentative support for the hypothesis that most subjects were making incremental adjustments to their problem redefinitions during the PMM cycle.

As stated earlier, the problem redefinition that subjects appear to have used in this investigation is different from the types of problem redefinitions proposed by both the incremental and the cybernetic models. The incremental problem redefinition implies that people only attend to the feedback loop that gives them information on the validity of their decision alternative. In addition, this decision making model proposes that problem redefinition occurs as a consequence of changes in the choice of the decision alternative, not by conscious thought, design or anticipation. For the incremental problem redefinition, subjects' changes in allocations to market research, quality control and so on could eventually, in and of themselves, lead to problem redefinition. It is argued that this is not the type of problem redefinition that occurred in the current study.

Subjects seem to have changed their patterns of allocation to the sets of organizational functions associated with particular problem definitions when problem redefinition was indicated. In other words, problem redefinition was a conscious or anticipated change in problem definition made by the decision makers. Decision makers monitored a unique set of variables to know when the situation changed so they could implement problem redefinition. In the present research, therefore, the changes in allocations to each individual organizational function were themselves a consequence of the subjects' planned problem redefinition.

The cybernetic model, on the other hand, says that problem redefinition is a distinct or quantum change in the definition of the problem. The results from the analysis of the relationship between the moving average of the industry sales slope and resource allocations and analysis of the plots of ratio allocations across time indicate that subjects were attending to the state variable when making their assessment of the validity of their problem definition. This supports the cybernetic paradigm's contention that decision makers attend to a unique set of variables that identify the decision situation. However, the results of the regression analysis of the relationship between the industry sales slope and resource allocations suggest that subjects were not making distinct or quantum changes in their problem definitions. This, of course, is contrary to the cybernetic theory's proposal that problem redefinition is a distinct change.

The problem redefinition that appears to have been used in this study by most of the subjects seems to be an incremental response by decision makers to perceived changes in the decision situation. This type of problem redefinition uniquely combines the second feedback loop from cybernetic theory with the principles of incrementalism in decision making that are proposed by the incremental paradigm. The third type of problem redefinition proposed here suggests that decision makers attend to a feedback loop specifically to assess the validity of their problem definition. If the feedback information indicates a change in the decision situation, the decision maker may make incremental adjustments to the problem definition to change the current definition to a new one. This process highlights an important cognitive role in the problem redefinition process that the current incremental model fails to include. The third type of problem redefinition, therefore, is a unique approach to problem redefinition that arises from a combination of cybernetic and incremental theory principles.

Future Research

Types of Problem Redefinition

This research was framed on the basis of the cybernetic decision making model which proposes that problem redefinition is a distinct and conscious decision made by decision makers in response to changes in the decision situation. The results of the investigation suggest that decision makers may respond to changes in the decision situation with conscious incremental changes in their definitions of the problem. It was argued here that this is a problem redefinition process different from those proposed by both the cybernetic and the incremental models of decision making. The identification of a third type of problem redefinition process raises some interesting research avenues for future investigations.

The argument was made here that there appear to be three types of problem redefinition processes. Future research should examine each one of these types of problem redefinitions. In particular, the third type of problem redefinition identified here should be the focus of more empirical investigation to confirm its existence since the data from this study can provide only tentative support for it. An important research question is to examine whether or not the three types of problem redefinition are competing processes. If they are, the relative effectiveness of each of these should be examined. If they are not, research should be concerned with identifying the circumstances under which each different problem redefinition process will be used. In other words, decision makers may use one type of problem redefinition under one set of circumstances and another type of problem redefinition under another set of circumstances. It is also possible that there are various patterns of use of the three types of problem redefinition across different groups of decision makers. Another research question is whether different people use different problem redefinition processes across all situations. If not, do different people use different problem redefinition processes in different situations? What individual difference variables relate to choices of different problem redefinition processes? These research questions can be guided by the extensive theoretical frameworks of both the cybernetic and the incremental models of decision making. However, both these frameworks must be adapted to explain the third process of problem redefinition identified by this research investigation.

Principles of Cybernetics

The cybernetic theory of decision making laid the theoretical groundwork for this research investigation. Although the results of this research suggest that subjects were not following the cybernetic problem redefinition process, there was support for other cybernetic principles. Subjects did use the state variable when making their problem redefinition decisions. However, post hoc analyses reveal that they did not use the changes in the slope of the industry sales curve at one time period to make their problem redefinition decision. Rather, they appear to have used a moving average of the industry sales slope. The results of this study raise numerous questions about the cybernetic framework for future research.

One of the first suggested by the current investigation is to explicitly examine the differences in decision making processes associated with the two different feedback loops. One of those differences concerns the differential use of case-specific and base rate information in relation to each of the two decision feedback loops. This issue should be directly examined. Another difference that should be the focus of future research is to determine whether or not decision makers use different information processing rules for each of the two feedback loops.

One of the primary post-hoc hypotheses presented in this discussion chapter has been that differences in type of information may have led to the unexpected findings about the impact of the primacy information processing variable. This post-hoc analysis should be empirically investigated to determine if different types of information are interpreted differently. Furthermore, research should examine whether the presence or absence of a particular type of information has a differential effect on decisions over time.

A second major issue for future research is to empirically test the impact of decision makers' implicit theories on problem reformulation decisions. In the current research, differences in implicit theories were controlled for by teaching subjects an explicit theory that they used to guide their problem redefinition decisions. This investigation would also provide empirical evidence on Steinbruner's (1974) contention that decision makers' implicit theories restrict the implementation of problem redefinition.

Earlier in this chapter, one of the sections discussed the nonsignificant findings for the regressions of the Introduction allocation ratio on the Control model (all the main effects) and each interaction term. In that section it was proposed that one of the reasons decision makers may not have used the information processing cues during the first part of the simulation was that people found the simulation too complex. It was noted that people may have started to use the information processing cues once they were comfortable with the simulation. This suggests another aspect of future research. Specifically, future research that attempts to investigate decision makers' implicit theories should empirically assess decision makers' propensity to use simple schemata for complex environments and complex schemata for simple environments.

Finally, researchers should attempt to identify which characteristics of the state variables decision makers are most likely to attend to when making their assessment of the validity of their problem definition. In an earlier chapter, it was proposed that decision makers' implicit theories guided their attention to specific characteristics of the state variable. The results of this research suggest that there may be a trend among decision makers about which characteristics of the state variable to monitor. Only an empirical investigation can confirm the existence of such a trend as well as determine if such trends also exist for other types of state variables.

Information Processing Rules and Problem Redefinition

The present investigation raises a number of future research paths for the more specific issue of the integration of information processing rules with the problem redefinition stage of decision making. This research suggests that some decision makers may use information processing rules when they are making incremental adjustments to their problem redefinition. This raises a number of important research questions. First, do people use information processing rules with each type of problem redefinition? If so, are the same information processing rules used for the three different types of problem redefinition? If not, research should attempt to find out which rules are used for which type of problem redefinition. In this situation, future research should also determine which information processing rules are more likely to lead to each type of problem redefinition. The current research results suggest that information processing rules may have some role in the process of problem redefinition. Future research should thoroughly investigate the existence of this role to gain a more detailed understanding of the problem redefinition processes.

A second research direction arises from the research design of the current study. Since this study was a within-subject design, it was not possible to draw generalizations about the use of information processing rules. A replication of this study with a larger sample size would allow the type of generalizations associated with cross-sectional studies.

Third, additional research should also investigate the impact of other information processing rules on the three types of problem redefinitions. Literature from information processing, heuristics and attribution theory provided the information processing rules used in this study. The research in these areas has largely been done in lab settings. As Markus and Zajonc (1985) point out, research done outside the normally-occurring, stimulus-rich social environment may exaggerate the effect of information processing cues. When the same cues are placed in an information-rich environment, the effect may dissipate for some decision makers or in certain conditions. This sequence of events may have occurred in the current research setting since the computer simulation was programmed to replicate a real-life business environment. This replication attempted to provide the decision maker with an environment rich in a variety of information. Since the decision maker had so much information at his/her disposal, the significance of the information processing rules may have decreased for some of the decision makers for all situations while other decision makers felt the need to use these rules only in certain situations. Based on the preceding argument, future research should explore inputs to the decision making process which have been previously investigated outside of the laboratory setting.

The primary purpose of this research was to identify the information processing determinants that led people to make problem redefinition decisions. The results suggest that different people may use different information processing rules. This finding is not unexpected since previous research has also found that different individuals use different information processing rules (Moch, Buchko and Rubin, 1987; Hogarth, 1980; Nisbett and Ross, 1980; Tversky and Kahneman, 1974). Steinbruner (1974) argues that individuals have access to the same information processing rules but do not necessarily use the same ones for the same situation. He contends that the different implicit theories that people use for the same situation lead to differential use of information processing rules.

In the current research, decision makers were taught the PMM theory in order to give them the same theory to use in the simulation. However, the decision makers were not taught how to use the information processing rules given in the situation. Therefore, they were free to rely on their own information processing schemata to decide which information processing rules to use or not to use. Future research should examine if individual difference characteristics cause a differential use of information processing cues among individuals doing the same problems. A further step along this same research path would be to investigate the relative effectiveness of different rules in improving decision performance.

In an earlier section of this chapter, it was suggested that decision makers may abandon the use of information processing rules when there is considerable uncertainty in the environment. Future research should examine decision makers' use of information processing cues in various environments and in unexpected situations to determine specifically when information processing cues are likely to be used in a problem reformulation decision and when they are not.

Finally, only one state variable was used in this research to satisfy the law of parsimony. The arguments made in this chapter regarding the differences of the effects of qualitatively different information on the decision making process call for further investigation of information processing rules under conditions of similar information. In other words, the impact of information processing rules on the relationship between problem redefinition and changes in the characteristics of the state variable should be investigated in situations where subjects get either case-specific or base-rate data, not both.

Having subjects process information on different state variables raises a whole new direction of research. First of all, what, if any, information processing cues are used by decision makers when making their problem redefinition decisions? Second, what characteristics of the different state variables are attended to in making the problem redefinition decision? Third, what do decision makers do if the state variables give them different information regarding the need to implement problem redefinition?

Future research should also attempt to resolve the methodological issue of concern here. Autocorrelation is a frequent threat in time series data (Neter, et al, 1985) and, as stated earlier, may affect the results of a longitudinal research investigation. One way to avoid autocorrelation in time series would be to create a decision situation where the current decision had no relationship to the previous decision situation. In this situation, the subject would be responding to random shocks programmed into the decision situation. An example of this would be to create a computer simulation where subjects had to evaluate the stock market for each quarter. Another type of research situation would be to look at decisions where subjects had to make binary problem redefinition situations. An example of this type of decision would be to create decision situations requiring medical diagnoses of patients who have one disease or another. Another type of research situation would be the buying and selling of stock on the stock market.

This chapter has taken a sweeping and speculative look at the implications of this investigation's findings, at possible theoretical explanations for the unsupported hypothesis and at the theoretical framework that generated the research hypotheses. The suggestions for future research, while speculative, are viable research avenues. The continuation of research on the topics of problem redefinition, cybernetic theory and the cognitive perspective of decision making is likely to lead to a detailed understanding of the cognitive aspects of the problem redefinition stage. In addition, the continuation of research on dynamic decision making is likely to lead to more applicable and generalizable theories of decision making.

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