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EXPERIENCE AND INFORMATION EFFECTS
ON SEARCH STRATEGIES IN A
CAPITAL BUDGETING TASK

By

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ABSTRACT

EXPERIENCE AND INFORMATION EFFECTS ON SEARCH STRATEGIES IN A CAPITAL BUDGETING TASK

By

Monte Ray Swain

The significance of capital budgeting to an organization's success makes the possibility of information impediments and individual biases in the decision process a particular concern. These potential confounds are exacerbated by the breadth of personnel experience typically found in the capital budgeting process. The research literature to date has not clearly determined potential effects of increasing information and past decision episodes on the capital investment decision task. Therefore, this study of experienced and inexperienced capital budgeters examines for information load, data fixation and functional fixation effects on information processing behavior. Results of this study are important to the design of capital budgeting decision support systems.

Two groups of participants were involved in this study. Thirty-six experienced capital budgeting professionals served as the study's experienced group. Forty-eight undergraduate students majoring in accounting or finance served as the study's inexperienced group. Six capital investment choice scenarios were sequentially presented on a computer to each participant. The computer randomly varied

the level of information attending each of the six choice task and traced the information search strategy employed by the participant for each task.

Three hypotheses were examined in this study. The first hypothesis examines the effect of information load on the information search strategy. Results of an analysis of variance (ANOVA) indicated that the study's experienced capital budgeters, compared to inexperienced capital budgeters, were relatively more systematic and exhaustive in their information search as the information load increased. The second hypothesis tests the carry-over effect of previous search strategies on the current search strategy (functional fixation). Results of path analysis indicated that the inexperienced capital budgeters' search strategy was dependent on previous search strategies. The third hypothesis investigates the carry-over effect of previous information loads on the current search strategy (data fixation). ANOVA found that the experienced capital budgeters' search strategy for a particular decision was more systematic and exhaustive when preceded by an unrelated capital investment decision with a high level of attending information.

This dissertation is dedicated to
my loving wife and best friend, Shannon.

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No one writes a dissertation alone. The irony of it, though, is that only one name can be on the cover. However, without the important support of many people, the work could not have been accomplished.

No dissertation committee could have proved themselves any more able and willing than has mine. Susan Haka, my chairperson, simply embodies every quality of a true scholar and mentor. She is a constant source of good advice when I am perplexed and encouragement when despondent. Always with an eye on the "big picture," if this study has anything important to say, much of the credit must go to her.

The presence of my other committee members, Gary Cook and Frank Boster, were also very important to this work. Gary provided the important use of his ISLab instrument and kept the focus on design implications for decision support systems. Frank simply has an amazing grasp of research design and statistical analysis issues.

I must also acknowledge the presence of an unofficial committee member. Harold Sollenberger's name is not on the official documents. However, without his encouragement and confidence and industry contacts, this work would have surely stalled. Additionally, the writer of a dissertation must have a colleague who will, at any time night or day, listen without judging, counsel without contempt, and laugh without restraint. My good friend, Bob Allen, proved himself to be such a colleague.

I thank the students at Michigan State University and the professionals listed in this work who so willing gave of their time and served as participants. I am particularly indebted to the Department of Accounting at Michigan State University and the Institute of Management Accountants (formerly the National Association of Accountants) for their important financial assistance.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION

1.0 Overview

In this first chapter, Section 1 is devoted to laying the groundwork for this study of decision processes involved in capital budgeting. In Section 2, the research questions are introduced. As presented in the third section, this study is anchored to a particular model of decision making. The usefulness of this model for developing decision support systems is also considered in Section 3. Contributions of this study are discussed in Section 4.

1.1 Groundwork

Outside of strategic planning, capital investment decisions probably are more important than any other challenge facing corporate management (Ferreira and Brooks, 1988). Capital budgeting has a direct and substantial impact on stockholder wealth and productivity in the economy. Consequently, it is not surprising that the subject of capital expenditure analysis has been the topic of much discussion over the past several decades. Normative decision models utilizing sophisticated capital budgeting tools such as discounted cash flow techniques and probability analysis are developed and recommended to industry. However, many firms are slow to incorporate these sophisticated tools. In 1976, Mintzberg, Raisinghani, and Theoret observed that:

> In capital budgeting as well as in less formal types of authorization, a major problem is presented by the fact that the choices are made by people who often do not fully comprehend the proposals presented to them. Thus in authorization the comparative ignorance of the manager is coupled with the inherent bias of the sponsor. This explains why empirical studies of capital budgeting have shown it to be a somewhat distorted, political process far less analytical than the normative literature suggests (1976, p. 260).

More recently, surveys of industry show that firms continue to utilize less-than-optimal approaches to capital budgeting (Bierman, 1986; Ferreira and Brooks, 1988; Pike and Sharp, 1989; Pike and Ho, 1991).

This study presents evidence that helps explain apparent discrepancies between prescribed and observed capital budgeting behaviors. It recognizes, as indicated by others such as Bower, that capital budgeting involves "intellectual activities of perception, analysis, and choice which are often subsumed under the rubric 'decision making'" (1970, p. 7). Therefore, this study supports efforts to integrate human information processing behavior in accounting information systems. Based on past results, Ko and Mock (1988) suggest that the utility of accounting information cannot be isolated from the information users and the cognitive characteristics of information users need to be considered in the design of accounting information systems. Further, Dickson, Sen and Chervany argue:

> In essence it is wrong to assume that all decision makers are the same and can effectively function with undifferentiated information systems. In particular, it is naive to assume that information system requirements do not vary for the type of decision being formulated (1977, p. 914).

Finally, in promoting work such as this study, Dickson et al. go on to recommend use of laboratory studies in the improvement of information system analysis and design.

Notable research indicates that the capital budgeting process can be significantly affected by the type and amount of information provided to the decision maker (see, for example, Gordon and Pinches, 1984; Haka, 1987; Iselin, 1988). As primary providers of information germane to the capital investment decision, accountants can influence directly the capital budgeting effectiveness of an organization. Therefore, accountants must understand the potential effects of both information presentation and information volume on the capital investment decision process (Gordon and Pinches, 1984).

1.2 Statement of the Research Questions

This study is part of a long line of work attempting to distinguish between models of the "Economic Man" and the "Administrative Man" (Klimoski, Kerr, Tollier and Glinow, 1975). The Economic Man follows a rational or normative decision process characterized by the following abilities:

- complete and consistent ranking of alternatives;
- awareness of all possible outcomes;
- performance of complex probabilistic computations;
- selection of the alternative that maximizes his utility.

Conversely, the Administrative Man is limited in his intellectual capabilities by the principle of *bounded rationality* (Simon, 1955). His decision abilities are characterized by the following:

- maximizing is replaced by *satisficing*;
- alternatives are evaluated through *problemistic search* processes that are simple-minded, sequential, and biased;
- repertories of decision action are developed and adhered to in recurrent situations;
- each action program is semi-independent of others.

Determining the reality of the decision maker is a difficult process. It likely that the actual decision maker fluctuates between the Economic Man model and the Administrative Man model based on changes in decision context and the attending information system and based on individual differences among types of decision makers.

Because of the complexity of choices and the potential cognitive limitations of decision makers, researchers such as Tversky and Kahneman (1986) have observed the propensity to make intransitive and inconsistent choices. Even at the societal level, the proliferation of financial accounting standards has raised concerns of information overload (American Institute of Certified Public Accountants, 1983). Hilton (1985) contends "Such characteristics of choice behavior may be expected to *affect both the type of information which should be provided to decision makers* and the way in which that information will be utilized once it is received" (p. 3, emphasis added). With greater insight into the choice behavior of individuals, accountants -- as providers of information to decision makers -- can enhance the effectiveness of capital budgeting. This improvement appears in more insightful management training, more effective organization design and more productive decision support systems (DSS).

Accounting researchers have become increasingly occupied with investigating underlying information processing strategies employed by decision makers in a variety of contexts. Specific topics, such as information load (Schick, Gordon and Haka, 1990), functional fixation (Haka, Friedman and Jones, 1986), data fixation (Barnes and Webb, 1986) and the expertise of the decision maker (Bouwman, 1985) have been particularly prominent within information processing research. Barnes and Webb (1986) comment that these topics originally had a singular appeal to management accounting and information systems. Lately, however, these issues have been addressed in forums outside of this context.[1]

This study investigates information load and fixation effects on decision makers within the critical managerial domain of capital budgeting. Additionally, researchers, such as Barnes and Webb (1986), note that little has been done to identify the impact of experience among decision makers by information load and fixation effects. Therefore, three research questions are addressed. First, how do increasing amounts of information affect the capital investment decision process? Second, what effects do previous capital investment decision tasks have on current capital investment decision strategies? Third, how are the issues raised in the previous two questions affected by different levels of experience?

1.3 A Decision-Making Model

Meads (1985) and Reneau and Grabski (1987) present an approach to research of accounting information systems postulating that the decision maker's interface with the information system is a function of JOB, USER and MACHINE factors (see Figure 1.1). Such an approach is helpful in understanding the nature of the capital budgeting DSS.

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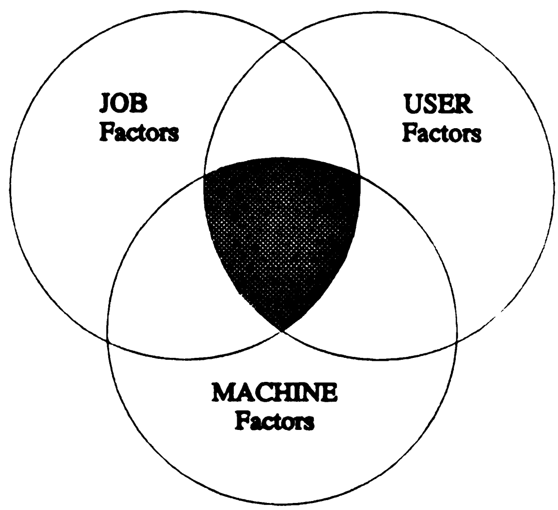
[1]Consider, for example, the recent Forum on Market's Fixation and Accounting Numbers in *The Accounting Review* (October 1990).

Figure 1.1

Factors Affecting the Capital Budgeting Process



Meads (1985) describes the JOB factor as generally relating to the task, training and social structure. This study focuses on the capital budgeting task. There are particular aspects of this task which engenders unique characteristics within this decision process in contrast to other types of decisions such as price-setting or loan analysis. Further, the amount of information attending the capital budgeting task changes as the decision maker moves among decision projects. Past research documents effects of information load on decision processes (Schick et al., 1990).

Additionally, the very movement of the decision maker among different capital investment projects creates concern about carry-over effects of previous, unrelated decision tasks on the current capital investment project. All three of these issues contribute to the JOB factor.

USER factors convey the effects of cognitive, physical, effective and motivation influences. Accounting system designers should evaluate a particular user's mental model before designing the DSS. This approach avoids limiting the effectiveness of the DSS as a result of user/system incompatibilities (Pei and Reneau, 1990). One important aspect relative to the USER factor is determination of intrinsic differences between experienced and inexperienced decision makers. Experience effects on decisions processes have been documented within decision task domains other than capital budgeting. These domains include, for example, financial statement analysis (Bouwman, 1985) and auditing (Frederick, 1991).

The final factor, MACHINE, refers to effects of hardware, software and documentation. As computerized information systems become an increasingly integral part of the business environment, there is concern for the effect these systems have on the capital budgeting process. Issues such as transition methods, memory aid structure, user/machine interaction styles and response time may have important influence on the decision process and should be considered in related research (Shneiderman, 1986). Research on decision processes that do not involve realistic information systems may not be generalizable to the current capital budgeting environment.

This study examines issues related to JOB and USER within a MACHINE environment. Reneau and Grabski (1987) contend that many inconsistent findings within research of accounting information systems can be explained by failure to examine the interaction between these variables. As seen in Figure 1.1, it is possible to examine each of these issues alone. However, reality demands that research should be centered on the interaction of these factors. This study is in harmony with such an approach. The JOB factor is developed on information load and carry-over effects within the capital budgeting task. The USER factor is concurrently examined for effects of capital budgeting experience. Mundane realism is promoted since these issues are manipulated and measured within a computerized information system environment (the MACHINE factor). By centering this study on the interaction of JOB, USER and MACHINE, much can be gained in the design of DSS specifically for the particular decision maker and decision task (Dickson et al., 1977).

1.4 Contributions

By providing additional insight into information load and fixation effects on decision processes within the domain of capital budgeting, this work makes two important contributions to accounting research. The first contribution is methodological. The effective development of computerized decision aids, i.e. DSS, requires a clear understanding of the human decision process *in a computer environment*. Previous research on the human decision process is limited as a result of using traditional data collection instruments, e.g., eye movement recordings and verbal protocol analysis. These techniques are foreign to the natural decision environment and potentially interfere with the decision process being observed. This research uses an adaptation of a computer program called ISLab (Information Search Laboratory) (Cook and Hershauer, 1987) to monitor interactive decision-making activity. Todd and Benbasat (1987) note that a research approach utilizing computer tracing is particularly applicable to DSS research. Data can be collected unobtrusively while the participant is using the system.

The second (and more important) contribution is theoretical. As stated above, this information processing study returns the issues of fixation and information load effects back to the management accounting and information systems context (see, for example, Ijiri, Jaedicke and

Knight, 1966; Ashton, 1974). In this context, this study presents important evidence regarding the interaction of information load and fixation trends with different types of capital budgeters.

No research has examined differences between inexperienced and experienced individuals regarding the information load and fixation effects on capital investment decisions. The decisions made regarding the acquisition, maintenance and abandonment of capital assets are extremely important to most companies. One would expect that these decisions be consigned to designated experts. The competitiveness and long-term viability of an organization is magnified by its ability to enhance the performance and training of both experienced and inexperienced decision makers involved in the capital budgeting process. To do this, the organization must first understand the relationship between information processing and experience. To develop such insight, this research theorizes and tests for systematic differences in information load and fixation effects on the information processing of experienced and inexperienced capital budgeters.

The results of this study indicate that increased information causes inexperienced capital budgeters to be less systematic and thorough in their decision process compared to experienced capital budgeters. Additionally, inexperienced capital budgeters display fixation on decision processes used in previous, unrelated capital budgeting tasks. On the other hand, experienced capital budgeters are affected by information attending previous, unrelated capital budgeting tasks.

1.5 Summary

This chapter introduced the research questions of interest in this study and presented some arguments for their importance. There are four chapters that follow. Chapter II is a literature review that locates the current study within the human decision-making research domain and develops testable hypotheses. Chapter III presents the methodology used in this study. Included in this chapter is a detailed description of the development and administration of the research instrument. The participants involved in the experiment are also described in Chapter III. Chapter IV describes the analysis performed and results of the analysis for each hypothesis. Finally, findings and implications are summarized, contributions and possible limitations are discussed and future research is suggested in Chapter V.

CHAPTER II

LITERATURE REVIEW

2.0 Overview

This chapter discusses some behavioral implications involved in contemporary capital budgeting and presents this study's hypotheses. The first section of this chapter describes the potential for information systems to impede the capital investment decision process. The second section introduces the need to understand behavioral processes when developing capital budgeting support systems for a decision environment characterized by a lack of structure. In Section 3, the particular decision process analyzed in this study, the information search strategy, is presented. The remaining sections describe factors that influence the information search strategy. These factors include the decision maker's level of experience (Section 4), the amount of information attending the decision (Section 5), and the decision maker's fixation on factors attending past decisions (Section 6). Past research has been unclear on the interactive effect of these factors on the information search strategy. Therefore, testable hypotheses related to these interactive effects are presented in Section 5 and Section 6.

2.1 Capital Budgeting

Kaufman (1986) comments that

> Any business is a series of capital investment projects. Each investment is an attempt to assure some facet of the company's future well-being. Viewed this way, *the subject of capital investment is the subject of business*. (p. 3, emphasis added)

The high level of time and resources typically committed make decisions on capital assets critical to most companies. Yet despite its crucial importance as a business function, capital budgeting typically has no organizational identity (Kaufman, 1986). There is no single department with responsibility for the ultimate content and success of the capital budget. This reality is seen in the existence of complex capital budgeting manuals and procedures. Companies exert great effort to control a process that, due to the principle of responsibility accounting, has become diffused over many individuals. And despite the standard policy that large outlays require higher-level authorization, a significantly large number of investment decisions is delegated by top management to comparatively inexperienced agents (Wheelwright, 1986). Therefore, the results of both experienced and inexperienced capital investment decision making has a material effect on the organization's prosperity.

Accountants have a comparative advantage in judgment/decision research (Demski and Swieringa, 1981) and should consider the effects that accounting context has on participants' underlying cognitive processes vis-a-vis the capital investment decision. Gordon and Pinches (1984) note "The existence of information system-related impediments creates a major stumbling block which inhibits the effective usage of sophisticated capital budgeting approaches" (p. 3). The accountant must be aware of the nature and effect of such impediments, which have the potential to vex the cognitive processes of the decision maker via the improper presentation of germane information. This is not a new concept to accountants as evidenced by Ackoff's (1967) well-known argument that most managers using a management information system suffer more from "an overabundance of irrelevant information [than they do from a] lack of relevant information" (p. 148).

2.2 Behavioral Decision Theory

In addition to decision impediments caused by improper information presentation, research has shown that both naive and knowledgeable individuals are prone to inherent biases in certain decision situations (see, for example, Tversky and Kahneman, 1983). Fischhoff (1982) proposes that the reduction of such undesirable biases requires some understanding of and hypotheses about peoples's cognitive processes. Organizations, therefore, are interested in the development of strategies that improve the important capital budgeting decision process.

Cognitive psychology (aimed at comprehending the decision-maker's mental processes) has had significant impact on accounting research (see, for example, Newell and Simon, 1972; Einhorn and Hogarth, 1981; Hogarth, 1991). Knowledge of human cognitive processes increases the ability of accountants to design effective DSS and other accounting information systems. One of the purposes of a capital budgeting information system is to provide useful and timely information to decision-makers. Therefore, it is important that those who furnish these systems understand how this information is used (and possibly abused) by decision makers (Ashton, 1974; Klimoski et al., 1975; Shields, 1983). The cognitive characteristics of information users need to be considered in the design of accounting information systems (Ko and Mock, 1988). Therefore, the design of effective capital budgeting information systems requires the integration of human information processing behavior theories with accounting system development.

2.2.1 Prescriptive theories. Einhorn and Hogarth (1981) carefully delineate issues revolving around prescriptive (optimal) and descriptive (observed) decision processes. Optimality is defined as "decisions or judgments that maximize some explicit and measurable criteria (for example, profits, error and time) *conditional on certain* *environmental assumptions and a specified time horizon*" (Einhorn and Hogarth, 1981, p. 55, their emphasis). Models abound to prescribe optimal managerial decisions, including the capital budgeting activity. However, multiple goals and multiple time horizons exist in realistic capital budgeting settings that can create difficulty in applying a strict prescriptive approach to accounting systems research and improvement of the capital investment decision (Joyce and Libby, 1981; Hong and Vogel, 1991). As an alternative, one first seeks to understand actual investment decision processes (the descriptive approach) before ascertaining the acceptability of the capital budgeting method to the organization. Then the accountant and the organization works to learn from the decision maker and/or improve the decision process.

2.2.2 Descriptive theories. There are realistic task complexities and natural constraints that inhibit the ability of the decision maker to utilize, for example, a Bayesian approach to decision making. The decision maker has both internal and external limits on knowledge and ability. As a result, when solving ill-structured decision tasks involving multiple criteria, the decision maker often make concessions (for example, a limited, rather than complete, investigation of alternatives). This satisficing approach (Simon, 1955) to decision making has been described as behaviorally grounded optimality (Keen, 1977).

Based on the bounded rationality concept, Hilton (1985) contends that where choice is difficult, complex and effort consumptive; it is characterized by some lack of consistency. Much of the bounded rationality concept is explained by conscious simplification of the choice processes. Therefore, as stated by Demski and Swieringa (1981), "Unaided human response is hardly to be trusted in all choice situations, just as the most elegant normative model possible is not to be trusted in all such situations" (p. 34). The task of creating an efficient computerized capital investment decision aid requires understanding human decision processes and how those processes can be best supported.

2.2.3 Decision structure. This study focuses on the human decision processes involved in capital budgeting. The issue, first, is to determine if (and when) capital budgeting becomes a difficult, complex and effort-consumptive process. Second, if this complexity results in inconsistent capital investment decision processes, this study seeks to understand the nature of this inconsistency --especially as it relates to levels of experience found in the organization.

Simon (1977) divides the decision process into three phases:

- o Intelligence -- searching, identifying and decomposing the problem.
- o Design -- inventing, developing, and analyzing possible courses of action.
- o Choice -- selecting a course of action from those available.

In a structured setting, the problem and important variables are defined. The unstructured task requires the decision maker to provide problem definition. The intelligence phase for a semi-structured task, though reasonably clear in problem definition, involves indeterminate key factors. However, guidelines are often available to help define the potential variables of critical interest.

In understanding the structure of the capital investment decision, it is useful to note Einhorn and Hogarth's (1981) discussion of choice versus judgment. While there may be similarities in the judgment process and choice process, Einhorn and Hogarth are careful to state that the choice task does not necessarily require implicit judgments on each alternative. Abdolmohammadi and Wright (1987), based on Simon's (1977) model, specify that the relationship between judgment and choice processes is a function of the complexity of the decision task. Table 2.1 (adapted from Abdolmohammadi and Wright, 1987) portrays the relationship of judgment and choice processes as a function of structure.

Table 2.1

Task Complexity and the Decision Process
(Adapted from Abdolmohammadi and Wright, 1987, Figure 1, p. 4)

	Decision Process		
Task Complexity	Intelligence	Design	Choice
Unstructured	Unique, undefined problem, few or new guidelines available	Infinite/undefined alternatives	Judgment & insights needed
Semi-structured	Repetitive, reasonably defined problem; guidelines available	Limited; specified alternatives	Judgment needed
Structured	Routine, well-defined problem & cues	Limited/well-specified alternatives	Little judgment needed

As seen in Table 2.1, as the complexity of the choice task increases, judgment and evaluation of alternatives becomes a critical feature of the choice process. This is an important observation since Abdolmohammadi and Wright (1987) suggest that the effects of decision maker experience will increase as the task becomes increasingly complex. Gordon, Miller and Mintzberg (1975) refer to three levels of decision making: (1) operating, (2) administrative, and (3) strategy. Operating capital budgeting decisions are highly structured and might include expenditures on such items as minor office equipment. Administrative capital budgeting decisions are semi-structured in nature and might include expenditures for replacing manufacturing equipment. Finally, strategic capital budgeting is largely unstructured and could involve expenditures on major equipment, the building of a new plant, or the purchase of an entire business (Gordon and Pinches, 1984).

All three levels of structure are found in the capital budgeting environment. Although operating, administrative and strategic capital budgeting processes are all important, the focus on this study is on administrative and strategic capital budgeting decisions. It is at these levels where judgment becomes critical and the effects of experience, an important element in current organizations, is expected to obtain. Additionally, a DSS plays its most important role with semi- and unstructured decisions (Keen and Scott Morton, 1978; Sprague, 1980)

When information impediments and individual differences exist within the firm's capital budgeting framework, the accountant must understand and orchestrate better capital budgeting via improved DSS. The level of the decision maker's experience plays an important role in how information affects the evaluation and decision process (Bouwman, 1985). Discerning the effects of experience and potential information impediments on information processing is an important first step to developing systems that enhance the investment decision process. Such research involves the process of generalizing psychological research findings into accounting contexts (Brown and Solomon, 1987).

2.3 Search Strategies

The decision process, as described by Simon (1977), is composed of several subprocesses: intelligence, design, and choice. The activity within each of these processes is complicated by the interaction of subprocesses. Understanding these interactions is important to the organization and coordination of capital budgeting. Gordon and Pinches (1984) note that research in the accounting, economics, and finance literature has emphasized the selection (or choice) phase of capital budgeting and suggest that more research efforts need to be placed on pre-selection processes (i.e. the intelligence and design phases). Haynes and Solomon (1962) comment:

> Our case studies suggest that the highest priorities should be assigned to the search for alternatives, the search for information, and the correct processing of the available data *before* ranking formulas are applied (p. 46, their emphasis).

An important premise of this paper is that accounting researchers can gain important insight into and improve the capital budgeting decision process (the prescriptive/ descriptive synthesis) through investigation of the information search and evaluation phase. As stated by King (1975) "The [capital investment decision] process is essentially one of search; search for ideas, search for information and search for decision criteria" (p. 80).

Before the selection of an investment alternative, information is gathered for each alternative. This information, related to each alternative in the choice set, are cues. Each cue is weighted according to perceived importance during the information evaluation (or information search) process before making a choice. The decision maker can use a combination of strategies when searching through the alternatives and their respective cues. Search strategy research is important since decision makers tend to search and process information consistent with the choice heuristic employed (Montgomery and Svenson, 1976).

The properties of a typical choice task include a set of alternatives defined over some list of specific attributes or dimensions, e.g., a group of potential employees described by grade point average (GPA), self-motivation, experience and desired salary. The decision-maker strategy for searching through the information set is generally dichotomized as compensatory and/or noncompensatory. A compensatory search strategy is a systematic and exhaustive search of all information where high values of some dimensions (e.g. significant experience) are allowed to compensate for low values of other dimensions (e.g. low GPA). Compensatory search strategies result in consistent choices that carry some connotation of optimality for a particular decision maker.

Noncompensatory search strategies capture Simon's satisficing/bounded rationality approach to decision making (Simon, 1977). In noncompensatory strategies, the evaluation can be heuristic-based and is more qualitative than quantitative. Since an alternative's favorable attributes usually cannot compensate for other unfavorable attributes, combinations across dimensions are avoided. The result is that the choice decision is not always consistent across alternatives. Similar to Hilton's (1985) probabilistic choice model, different iterations of the same choice task may result in a different decision.

Since the search strategy affects the decision made, accounting system designers can foster use of particular decision processes via manipulation of the factors affecting use of compensatory or noncompensatory information search models (Cook, 1987). Examples of models that fall within each of these two general categories follow.

2.3.1 Compensatory search strategies. Tversky (1969) discusses two forms of compensatory strategies -- the additive model and the additive-difference model. In the additive model, the decision maker primarily sums the dimensions within an alternative after assigning each dimension a score according to its value and a weight according to its relative importance. After weighing and summing the entire information set, the alternative with the highest score is chosen.

The additive-difference model is similar to the additive model. Yet rather than valuing all alternatives and comparing them at the same time, the decision maker will weigh and sum dimensions within two alternatives, choose the better alternative and then compare it to a third alternative (after weighing and summing its dimensions) until all alternatives have been evaluated. Either strategy should consistently result in the same decision. The additive-difference model revolves around a systematic search by dimensions (intradimensional) compared to the systematic interdimensional search characteristic of the additive model. Both models display little variance in the search through the sets of dimensions or alternatives, respectively.

2.3.2 Noncompensatory search strategies. There are many forms/models of noncompensatory strategies. Klayman (1983) discusses several, including the two most commonly cited noncompensatory models -- the conjunctive model and the elimination-by-aspects (EBA) model.

The conjunctive model depicts a search strategy through (possibly) random-ordered alternatives. As soon as an alternative is examined which meets a certain criteria level established for each dimension, the search is concluded and that alternative is chosen. Therefore, the approach may result in different decisions depending on the order the alternatives are examined (interdimensional search). This model is traditionally linked with Simon's (1977) theory of satisficing.

In the EBA model, the decision maker selects some dimension possibly based on its importance to the task or on the ability to quantify its value easily. This dimension is then highlighted and evaluated across alternatives. If this intradimensional search fails to determine a superior alternative, a second dimension is selected and examined across remaining alternatives not eliminated by the first dimension evaluation, and so forth (Tversky, 1972). In contrast to the conjunctive model, changing the priority order of the *dimensions* searched may affect the final decision in an EBA search strategy. Both the conjunctive model and the EBA model display a large amount of variance in the search of sets and subsets of alternatives and dimensions. Klayman (1983) and Biggs, Bedard, Gaber and Linsmeier (1985) contrast these four major types information search strategies in terms of the variables described above. Table 2.2, (adapted from Cook, 1987) summarizes the differences among these models.

Table 2.2

Contrasting Different Information Search Strategies
(Adapted from Cook, 1987, Table 3, p. 54)

SEARCH STRATEGIES	Proportion Searched	Variability by Alternative	Variability by Dimension	Search Direction
Compensatory				
Additive	high	low	low	interdimensional
Additive-difference	high	low	low	intradimensional
Noncompensatory				
Conjunctive	low	high	high	interdimensional
EBA	low	high	high	intradimensional

The four characteristics used in Table 2.2 (proportion searched, variability by alternative, variability by dimension and search direction) are used in this research as the operationalization of the decision maker's information search strategy. Exact definitions of these four information search strategy indicators follow in Chapter III.

2.4 Experience

2.4.1 Experience versus expertise. In reality, experience and expertise are not dichotomous factors, but are continuous. However, difficulty in scaling experience and expertise forces generalizable discussion back to some type of nominal scale, e.g., student, staff, and manager (Libby and Frederick, 1990). Additionally, researchers such as Davis and Solomon (1989) and Bonner and Lewis (1990) are careful to distinguish between experience and expertise. Expertise within a certain decision type requires both knowledge and ability. An individual involved in capital budgeting for several years may not have developed expertise for a particular type of capital budgeting task. In fact, rather than using traditional indicators such as number of years or position in the organization, Bonner and Lewis (1990) have proposed methods of testing for expertise with direct performance measurements.

Gibbins (1988) suggests that decision makers use a learning structure that carries them through the following four levels:

- Naive-as-to-task judgment
- Educated-as-to-task judgment
- Experienced-as-to-task judgment
- Expert-as-to-task judgment

This study makes some effort to directly evaluate acceptable levels of capital budgeting knowledge. However, direct testing for "expertise" (differentiable from "experience") in capital budgeting is not a focus of this study. Instead of measuring performance, the focus is the problem-solving process engendered by experience. In light of Gibbins' scale of decision task learning, the dividing line of interest for this study falls between educated- and experienced-as-to-task judgment.

It is reasonable to assume that personnel assignments within organizations follow a pattern of associating increasing experience with increasingly nonroutine capital budgeting tasks. Thus, less experienced employees are involved in well-structured operating capital budgeting while more experienced employees are involved in less-structured administrative and strategic capital budgeting that require increased amounts of judgment (Abdolmohammadi and Wright, 1987). Therefore, to differentiate experienced capital budgeters from those simply educated in capital budgeting techniques, this study utilizes participants experienced in capital budgeting at the administrative and strategic level.

2.4.2 Knowledge structures. Gibbins (1988) depicts educated decision makers as having developed a conscious knowledge structure for the task. However, this structure is constructed in response to the incentives and constraints of the learning situation (e.g. the classroom), not those of the actual task. Experienced decision makers' knowledge structures are much less conscious than at the educated stage, perhaps even automatic. Experienced knowledge structures have evolved from the educated stage, as some previously learned structures have been forgotten because they were not helpful in the specific task and/or other structures will have been incorporated.

Research has shown that experience in a specific decision domain engenders utilization of sophisticated knowledge organization (Libby, 1981; Frederick, 1991). It is these seasoned knowledge organizations or mental models that lead to significant differences in information processing between experienced and inexperienced decision makers (Bouwman, 1985; Iselin, 1989; Hershey, Walsh, Read and Chulef, 1990; Frederick, 1991). Frederick (1991), for instance, observes differences in knowledge structures between auditors and auditing students. Auditors demonstrate a greater development and dependence on schematic knowledge organizations. His results suggest that experienced auditors utilize advanced knowledge structures. These knowledge structures can expedite efficient and effective manipulations of information attending each decision situation. Frederick's conclusions are in agreement with accepted studies of cognizance and memory rank structures (Minsky, 1975; Wickelgren, 1981; Tulving, 1985).

On the other hand, as Marchant (1990) points out, the development of a large structured knowledge base enables the experienced decision maker to exhibit superior performance. However, the mental costs of such a knowledge base has associated costs which may on occasion lead to situations where inexperienced decision makers outperform experienced decision makers! Additional results obtained in the Frederick (1991) study suggest that such a situation is possible. It is expected that experienced capital budgeters exhibit enhanced knowledge organizations as compared to capital budgeting students. Therefore, the results seen in audit research such as Frederick's has similar implications for the capital budgeting arena.

Expert decision makers in other domains have also been examined such as physicians (Johnson, Hassebrock, Duran and Moller, 1982), financial investors (Bouwman, 1985) and managers (Stahl and Zimmerer, 1984). The evidence suggests that experienced participants in these disciplines do process information differently than inexperienced participants. Plans of attack, information assessments and general knowledge application appear to differ fundamentally between experienced and inexperienced decision makers (Gibbins, 1988; Anderson, 1988; Libby and Frederick, 1990).

2.4.3 Experience in the organization. Organizations recognize the value of experienced decision makers, particularly in the arena of capital investment. Large amounts of resources are often dedicated to the enhancement of skilled decision making or the training of novice decision makers via development of DSS or expert systems, respectively (Turban, 1990). The training of inexperienced capital budgeters or the direct enhancement of experienced capital budgeting requires that reliable methods for identifying performance differences across different experience levels be developed (Anderson, 1988; Smith, 1988). Additionally, research into the design of accounting information systems requires a focus on potential novice and expert differences in choice processes. This work responds to calls for research that addresses such issues conducted in an information system setting using actual capital budgeters (Reneau and Grabski, 1987).

2.5 Information

Designers of capital investment DSS should be aware of the implications that attend a decision maker's adherence to a particular information search strategy. Information search strategies are a function of several factors that may or may not be directly controllable by the DSS designer. For example, the decision maker's level of capital budgeting experience is not directly controllable by the designer, yet may have an effect on the information search strategy. On the other hand, the amount of information attending the task is at least partly controlled by the DSS designer.

Past research (e.g. Biggs et al., 1985) concludes that search strategies are a function of information load. Therefore, determining the manner and amount of information to be presented in a capital investment DSS is important (Einhorn and Hogarth, 1981). Further, when novice and experienced capital budgeters demonstrate systematic differences in their response to information sets presented by the decision aid, accounting researchers and practitioners can then develop systems that (1) train novices to act like experts or (2) actually augment the performance of experienced capital budgeters.

2.5.1 Information overload. Much of the accounting research on information load effects on decision making is based on Schroder, Driver and Streufert (1967) who describe the relationship between an individual's level of information processing and decision complexity as an inverted-U function. Drawing on their work, accounting researchers define decision complexity loosely to mean information load (Schick et al., 1990) and a large amount of research has followed focusing on such information load effects (Ashton, 1974; Snowball, 1980; Shields, 1980, 1983; Iselin 1988, 1989; Chewning and Harrell 1990). However, the definition of information load has generated some confusion. Schick et al. (1990) are careful to disengage their definition and operationalization of information *overload* from other research that is actually focused on consequences of information *load*. The inverted-U function of Schroder et al. (1967) is more closely related to the concept of overload which, as established by Schick et al. (1990), is the point where information processing demands on time exceed the amount of time or capacity an individual allocates to process information. The focus of information overload research is to determine the optimal interaction of an individual's information processing demands and task complexity. This interaction is seen in the effects on *decision quality* as a result of manipulating information load.

2.5.2 Information load. Conversely, information load studies investigate the effects of task complexity on *decision strategies* used by a decision maker (Libby, 1981; Ko and Mock, 1988). Research results have consistently found that information processing strategies leading to choice will vary as a function of task complexity (Jacoby, Speller and Kohn, 1974, Biggs et al., 1985; Cook and Hershauer, 1989). For this study, task complexity is varied by manipulating the number of alternatives in the choice set and by manipulating the number of dimensions of information used to define an alternative (Payne, 1976, 1982). The focus is the effects on *information search strategy* as a result of varying information load.

Typically, research in the past on information load has manipulated the independent variable "Information Load" simply by the total number of information inputs or cues provided to a decision maker (e.g. Jacoby et al., 1974; Payne, 1976; Biggs et al., 1985; Cook and Hershauer, 1989). If a decision maker has a set of cues attending a choice task, some of these cues represent different dimensions while other cues represent repeated dimensions. Using the personnel selection decision as an example, assume the following cue set (Figure 2.1):

Figure 2.1

Example of Information Load in a Choice Task

	DIMENSIONS		
INDIVIDUAL	GPA	Level of Experience	Desired Salary
A	3.2	Low	$28,000
B	3.5	Average	$32,000
C	2.7	High	$32,000

Here are three alternatives and three dimensions attending each alternative for a total of nine (3x3) cues. To add a fourth alternative (e.g. Individual D) to the cue set would increase the information load attending this choice task by three repeated dimensions. Information load is now 12 cues. Adding a fourth dimension (e.g. Self-Motivation) also would increase the information load (assuming the original three alternatives) by three.

2.5.3 Information density. Traditionally, research related to this study does not differentiate between increases of information load via increased alternatives or increased dimensions. However, Wilkie (1974) asserts it is important to distinguish closely between number of alternatives and number of dimensions per alternative in both analyzing and drawing conclusions from research data. One reason it is important to carefully distinguish between effects of alternatives versus dimensions is that the levels of alternatives versus dimensions attending a decision task are not equally controllable by the capital budgeting DSS designers. For example, the number of dimensions the DSS designer can develop and present to the capital budgeter is constrained by the total amount of information available for the set of alternatives. Secondly, the DSS designer can not solely determine the number of alternatives presented in the decision task. The number of alternatives secured for consideration is a function of practicality and availability.

Another reason researchers must distinguish closely between number of alternatives and number of dimensions per alternative is that these two sources of variance in the total amount of information attending a capital investment decision are not conceptually comparable. Iselin (1988, 1989) presents evidence that once a decision maker has conceived of one dimension (e.g. experience), it is much easier for him/her to conceive of additional values of that dimension as new alternatives are added to the cue set, than it is to conceive of a new and entirely different dimension (e.g. skill level, alma mater, etc.). In light of this study, such a phenomenon seems particularly true if the capital budgeter adheres to a interdimensional-type information search strategy, such as the additive or the conjunctive model (refer to Table 2.2). Expanding the number of dimensions requires the decision maker to operationalize and compare new concepts. Expanding the number of alternatives simply provides additional values of the same dimensions and would not require the same cognitive effort.

On the other hand, the relationship may reverse for capital budgeters utilizing an intradimensional-type information search strategy, such as the additive-difference or the EBA model. Additional dimensions, if not considered consequential by the capital budgeter, may not be evaluated at all. Therefore, adding new alternatives would cause comparatively greater cognitive effort as compared to dimensions not considered at all by the decision maker.

In this study, the effect described above is referred to as the density effect -- the information load effect of dimensions and alternatives are not expected to be of equal weight or density. Specific movements in the information search strategy as a function of a density effect are not posited in this study. However, when analyzing the effects of information load on search strategy in the capital investment task, this study is designed to control for potential density effects by differentiating between changing levels of alternatives versus changing levels of dimensions.

2.5.4 <u>Information load hypothesis</u>. This study postulates that systematically different information search strategies employed in capital budgeting are expected between experienced and inexperienced decision makers. Where such differences are present and observable, the organization should then be able to enhance desirable tendencies and offset negative biases, resulting in more effective capital investing. These experienced-as-to-task and educated-as-to-task distinctions are seen in movements between compensatory and noncompensatory search strategies as task complexity varies. Movement from compensatory to noncompensatory strategies is indicated by a decrease in the amount of information searched (Biggs et al., 1985). Additionally, this same movement reveals increased variation in the amount of information examined across decision alternatives (Payne, 1976) and across dimensions or attributes describing each alternative (Klayman, 1983). Finally, the direction of the information search, either interdimensional or intradimensional, provides insight into the individual's search strategy (Klayman, 1983; Cook, 1987). The reader is advised to review Table 2.2 for a summary of indicators of information search strategies.

Regarding the interaction of information load and search strategies among experienced and inexperienced decision makers, opinion in the literature is inconclusive. In general, as the amount of information attending a choice task increases, noncompensatory (versus compensatory) models of information search are employed (Payne, 1976; Biggs et al., 1985; Anderson, 1988). Past research related to information search strategies presents evidence that experienced individuals engage in less information search (indicative of noncompensatory strategies) than inexperienced decision makers (Johnson, 1985). Conversely, inexperienced individuals are often more systematic, thorough and sequential in their data search (indicative of compensatory strategies) (Biggs and Mock, 1983; Krogstad, Ettenson and Shanteau, 1984).

On the other hand, cognitive psychological research finds that decision experience results in an increased ability to use complex information patterns effectively to hold and manipulate larger quantities of information (DeGroot, 1965; Schroder et al., 1967; Newell and Simon, 1972). Thus, capital budgeting experience results in an increased capacity to hold and evaluate information. Experienced capital budgeters, as suggested by this research, engage in more exhaustive information search. In addition to increased information search, Hershey et al. (1990) suggest that experienced decision makers are more sequential in their information search strategy. This body of research, in contrast, would propose that experience engenders compensatory search strategies.

It is difficult, therefore, to know how past research applies to the varying levels of individual experience operating in the capital budgeting context. It is only clear that experienced and inexperienced capital investment decision makers should display systematically different information search strategies. The direction of the difference is not clear. Additionally, the effect of *changing* information load (a function of both the organization and the decision task environment) on the search strategies of novice versus experienced capital budgeters is unclear. This information would be useful to designers of DSS for capital investment decisions who can then work to enhance the abilities of capital budgeters across many classes of experience.

The following null hypothesis, called Hypothesis 1, is examined:

> **H_1:** Experienced and inexperienced capital budgeters do not display systematic differences in their *information search strategy* based on changes in *information load* attending the contemporary capital investment decision.

If this null hypothesis is rejected, the nature of the rejection is further examined for clarification of conflicting theory as it applies to capital budgeting. If experienced decision makers have a tendency to process larger quantities of information compared to novices (DeGroot, 1965; Newell and Simon, 1972), then one would observe that experienced participants exhibit greater adherence to compensatory information search strategies as information load increases. The opposing theory is increased experience allows effective shifting to potentially efficient noncompensatory strategies as information load increases (Biggs and Mock, 1983; Bouwman, 1985). This theory is applicable to capital budgeting if only the experiment's less-experienced participants hold to compensatory search strategies as information load increases.

As seen in Table 2.2, previous research has espoused that four variables serve as indicators of the "Information Search Strategy" factor: proportion searched, variability by alternatives, variability by dimensions and search direction. Factor analysis is used to determine if these four variables combine to form a unidimensional measure of information search strategy. The Information Load factor is carefully differentiated across changes in levels of alternatives and levels of dimensions to control for the density effect discussed above. A mixed-design ANOVA is initially used to analyze the results. Exact variable definitions and the experimental design is discussed in the methodology chapter (Chapter III).

2.6 Fixation

Capital budgeters are biased in their information search strategy by the amount of information attending the decision task. The capital investment information search strategy also is influenced by carry-over effects from previous, unrelated capital investment decisions. The notion that an individual's prior use of an object dissimilar to that required by a present decision task might impede that individual's ability to use the tool effectively has been a part of the cognitive psychology arena for many years (e.g. Duncker 1945; Adamson, 1952; Knight, 1960).

Ijiri et al. (1966) first applied the psychological theory of functional fixation to accounting and suggested that under certain circumstances, a decision maker might be unable to adjust his choice process to a change in the accounting process that supplies him with decision data. Haka et al. (1986) note "Accounting research on functional fixation has provided evidence of such a 'conditioning' response to certain accounting procedures" (p. 457). Researchers have tested the theories of functional fixation and found evidence of decision makers who continued "to reflect elements of past behavior -- which should have been forgotten" (Chang and Birnberg, 1977, p. 311). Previous research has suggested the existence of systematic differences in functional fixation effects between novice and expert decision makers within an accounting context (Haka et al., 1986).

2.6.1 Functional fixation. There is some contention in the literature that accounting research has not been particularly pure in its coupling with the functional fixation literature in psychology (Moon, 1990). For instance, Knight (1960) investigated the effect of successfully solving n water jug problems on the problem solving techniques used in trial n+1. He found that a series of successes caused the participant to persist in his earlier behavior and inhibited his ability to see the alternative (correct) approach. Additionally, Knight found that functional fixation sometimes resulted in correct solutions that were needlessly complex (Wilner and Birnberg, 1986). In this case, the decision maker is fixated on using a particular technique or function in addressing problem sets. This research approach is comparable to Haka et al. (1986) who examine preferences for suboptimal cost- or income-based techniques compared to optimal market price-based techniques by decision makers with a cost or an income orientation. Also commensurate with traditional psychology definitions of functional fixation is Moon's (1990) work investigating the use of cost cards in making incremental costing decisions after experiencing the technique of using the same information for inventory valuation.

2.6.2 Data fixation. On the other hand, a large set of accounting research investigates fixation on historic *data* rather than historic technique or *function*. Data fixation effects on individual decision making have been examined within the context of (1) product pricing based on full versus variable cost data (Ashton, 1976) or straight-line versus accelerated depreciation data (Bloom, Elgers and Murray, 1984), (2) variance analysis based on inaccurate versus accurate standards (Chang and Birnberg, 1977) and (3) project selection based on full versus variable cost data (Barnes and Webb, 1986).

However, this dichotomy, functional fixation versus data fixation, has not been clearly addressed in the accounting literature. Practitioners and researchers interested in understanding the human decision-making process as it relates to capital budgeting need to be aware of possible fixation effects. When search strategies exhibit time-series characteristics, researchers are left questioning whether it is functional fixation or data fixation (or both) which obtains. A proper knowledge of these effects must proceed the ability to counter potential biases and information impediments.

2.6.3 Fixation Hypotheses. This research posits that the decision maker is fixated on search strategies used in prior capital budgeting choice tasks (functional fixation) and/or fixated on data sets attending prior choices (data fixation), either of which may impede the use of a more effective search strategy in later decisions. The instrument and analysis methods employed in this study are able to distinguish between search strategies that are functional or data fixated. Additionally, the analysis determines if these effects are attenuated by the individual's level of experience in capital budgeting. Therefore, in addition to the information load concept discussed above, the strategy chosen to search information attending a specific decision is a function of the *search strategy* used in the decision maker's most recent decision. The search strategy attending the current decision may also be a function of the *information load* attending the prior decision.

The relationship between experience and functional/data fixation is not well understood. Haka et al. (1986) have suggested the possibility that categorical decision making experience may foster functional fixation. Gibbins states "It is not clear that experience in making judgments produces 'improved' knowledge structures: bad habits may be uncorrected, or even reinforced" (1988, p. 53-54). Recent research has shown that increased experiences can, at times, lead to decreased decision-making performance (Davis and Solomon, 1989). For example, Frensch and Sternberg (1989) demonstrate that, when a task demands restructuring of existing knowledge and the size of the mental knowledge base is large, problem solving can become less flexible. The result is that expert performance may not always follow experience, that is, experienced decision makers become fixated. In such a setting, it would be beneficial to develop decision aids or adopt other organizational approaches to reduce the likelihood of these adverse events.

On the other hand, Paquette and Kida (1988) and Barnes and Webb (1986) obtain experimental results indicating that experts can effectively shift to more efficient processing strategies when faced with complex decision tasks. These results agree with researchers such as Showers and Cantor (1985) and Shanteau (1984) who observe decision-making abilities unique to experts such as significant knowledge levels, well-organized knowledge structure, efficient processing ability and the capability to exercise cognizant control over their information and choice processing. Thus, novice decision makers would be more inclined to exhibit functional fixation compared to experienced decision makers. Hence, research is split on the ability of experience to promote or subdue fixation. Similar to information load effects, more testing on fixation effects is required to understand the causal relationship between experience and information search strategies vis-a-vis capital budgeting. A detailed understanding of these processes provides valuable understanding of the transition to experienced capital investment decision maker.

Null Hypotheses 2 and 3 (H_2 and H_3) are presented to test for the ability of capital budgeting experience to attenuate functional and/or data fixation effects. The factors Information Search Strategy and Information Load continue to be operationalized and analyzed in the same manner as in H_1.

H_2: Experienced and inexperienced capital budgeters are not differently affected in their *contemporary* capital investment *information search strategy* by the utilization of *past* capital investment *information search strategies* (i.e. Functional Fixation).

H_3: Experienced and inexperienced capital budgeters are not differently affected in their *contemporary* capital investment *information search strategy* by the *information load* attending *past* capital investment decisions (i.e. Data Fixation).

A rejection of either of these null hypotheses is further examined for its particular direction. This additional analysis should enlighten conflicting theory as it applies to various levels of experience in the capital budgeting process. If experienced capital budgeters are comparatively fixated on either their search strategies or on historic information loads, then research that proposes the habit-forming nature of experience (Haka et al., 1986; Gibbins, 1988) is supported for this decision type. On the other hand, if inexperienced capital budgeters display greater time-series dependencies, then the theory that experience engenders ability to control fixation (Showers and Cantor, 1985; Paquette and Kida, 1988) seems applicable to this decision context.

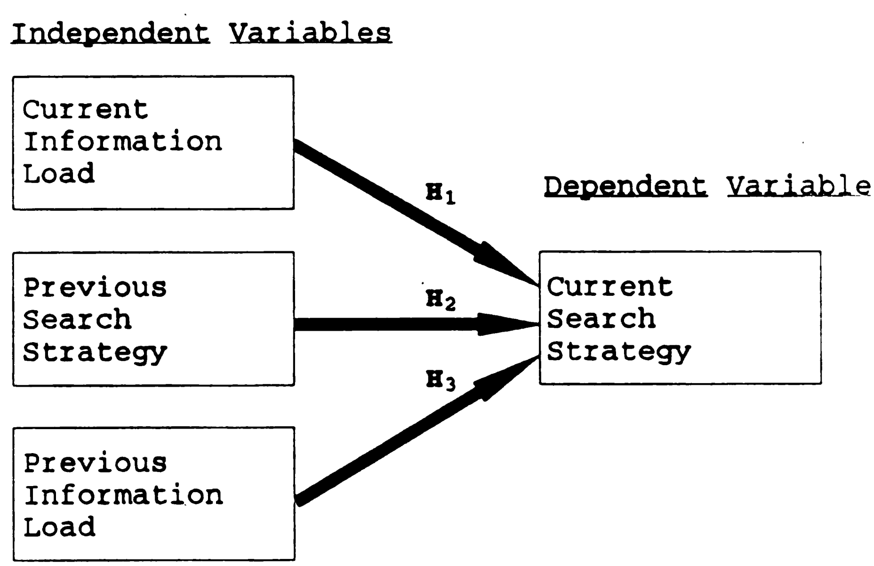
2.7 Summary

This chapter reviewed research regarding the behavioral implications of supporting the capital budgeting process. A brief discussion of capital budgeting within organizations -- emphasizing the divergence of experience and the potential of information system hindrance -- was presented in Section 1. In Section 2, the need for descriptive theories of capital budgeting was described. This need was specifically related to behavioral decision processes in semi-structured and unstructured capital budgeting tasks. Information search strategies, one specific aspect of the capital investment decision process, is the particular focus of this study. Descriptions and examples of various models of information search strategies were given in the third section of this chapter. In the fourth section, theories relevant to experience and expertise were submitted and related to the capital budgeting domain. Distinguishing information load from information overload effects on decision making based on previous accounting research has been somewhat difficult. Distinguishing functional fixation from data fixation has also been difficult. Specific definitions for these two categories of effects vis-a-vis the current study were presented in Section 5 and Section 6, respectively.

This chapter also presented this study's hypotheses testing the interaction of capital budgeting experience with the potential effects of information load, functional fixation, and data fixation on the information search strategy. The information load hypothesis (**H_1**) is presented in Section 5. The functional fixation and data fixation hypotheses (**H_2** and **H_3**, respectively) are presented in Section 6. For comparative purposes, the interrelations among the three hypotheses are depicted in the following diagram (Figure 2.2):

Figure 2.2

Interrelations of Variables within the Hypotheses



H_1 captures the effects of information load attending a decision task on the information search strategy utilized. H_2 and H_3 combine the information load question with studies on fixation by examining effects of previous information search strategies and/or information loads on the current task. These three hypotheses are subsequently examined in a two-stage experiment. The specific methodology utilized by this two-stage experiment is described in the following chapter. Specific results of the experiment are presented and analyzed in Chapter IV.

CHAPTER III

METHODOLOGY

3.0 Overview

The purpose of Chapter III is to discuss the hypotheses test procedures. A laboratory experiment is used to contrast information search strategies of experienced industrial capital budgeters and upper-division accounting students. Capital investment decisions are presented in a computer environment. The computer manipulates the information load attending a random order of capital investment decision tasks. The computer then traces the participant's information search strategy.

The first section presents an overview of the two-stage experiment and discusses the research design employed. The second section provides the two participant group's demographics. The third section is a detailed discussion of the capital budgeting task. The fourth section describes the research instrument, ISLab. Methods utilized in hypotheses testing are presented in the fifth section.

3.1 Experimental Design

To test the three hypotheses presented in Chapter III, this study utilizes two groups of participants, experienced and inexperienced capital budgeters. Each participant works through a set of capital investment choice tasks as presented on a computer screen. While tracking the participant's response, the computer manipulates the level of dimensions accompanying each choice task. The number of potential alternatives is fixed across all tasks for each subject.

As discussed in section 2.4.3, it is expected that as information attending a decision task expands by alternatives, the shock to the decision making search strategy is not as severe as expanding by dimensions (Iselin, 1988, 1989). Expanding the choice task by dimensions actually introduces additional *concepts* to the task and sharply increases the diversity of the attending information (the density effect). To control for the density effect, the design for this research is a mixed within/between-subjects approach (Keppel, 1982). The level of alternatives is considered an independent groups factor with the level of dimensions serving as a repeated measure. The logic of this design is discussed in Section 3.5.2.

To test for experience effects, experience and inexperience are used as a blocking variable. Therefore, this study has one within-subject factor and two between-subject factors, a 2 x 3 x (3) mixed factorial design. The within-subject factor is the number of dimensions (either three, five or seven) attending each capital investment choice task. The first between-subject factor is the participant's level of capital budgeting experience, either experienced or inexperienced. The second between-subject factor is the number of alternatives (either three, five or seven) from which the participant must choose for each choice task. The research design, including the number of observations gathered, is illustrated in Figure 3.1. The six choice tasks are randomized with a constraint so each cell has two observations per participant. Further discussion of how the experiment participant set was developed follows in the next section.

Figure 3.1

The Research Design

Actual number of observations per cell
(two observations per participant) is included

	3 Dimensions	**5 Dimensions**	**7 Dimensions**
3 Alternatives Inexperience	34	34	34
Experience	26	26	26
5 Alternatives Inexperience	32	32	32
Experience	22	22	22
7 Alternatives Inexperience	30	30	30
Experience	24	24	24

3.2 Participants

3.2.1 Experienced participants. To develop a sample of experienced capital budgeters, an executive MBA course was solicited for industry contacts. Subsequent correspondence established several companies' willingness to participate. In research of this type, it is essential that a clear dichotomy of experience and inexperience among the participant groups be established. Therefore, the experimenter consulted with the management at each company to develop a group of participants with at least one year experience in the capital budgeting process. Depending on the size of the company and its capital budgeting department, participating company-wide groups ranged in size from one to seven individuals. Actual on-site testing of these industry participants took place over a period of one month.

A total of 40[2] experienced decision makers from various industries took part in this experiment. Of this group, 36 participants provided usable responses. The enlisted companies are described in Table 3.1. As seen by the SIC descriptions used in Table 3.1, these companies cover a broad range of industries with a heavy concentration in the automotive production and distribution industry. Annual sales among these firms ranges from $4 million to

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[2] Originally, forty-six participants from industry performed the ISLab experiment. However, subsequent analysis of the data revealed that six of these participants did not have significant experience (at least one year) in capital budgeting. These six participants were deleted from the sample.

$127 billion. The participants from these companies have experience in capital investing activities ranging in magnitude from sixty thousand to three billion dollars. However, although the sample selection method is not random, it is expected that the industry participants in this study are generally representative of traditional capital budgeting management teams for heavily capitalized industries.

Table 3.1

Participating Companies in the Experiment

NAME	INDUSTRY	ANNUAL SALES (1990) (000's)	NUMBER OF PARTICIPANTS
Anderson-Cook, Inc.	Spline Rolling Machining	$ 13,000	1
BASF Corp.	Industrial Chemicals	5,420,000	1
Beaumont Hospital	General Surgery	326,300	3
Chrysler Corp.	Auto Assembly	36,100,000	2
Consumers Power Company	Electric Power	2,920,000	3
Delco Electronics	Auto Electronics	4,000,000	4
Ford Motor Company	Auto Assembly	96,000,000	6
General Magnetics	Electrical Supplies	12,000	1
General Motors Corp.	Auto Assembly	127,000,000	7
Leaseway Transportation	Auto Delivery	11,800,000	4
Michigan Opera Theater	Stage Performances	4,000	1
Nascote Industries	Auto Bumpers	112,000	2
U.S. Manufacturing	Auto Axles & Steering	54,000	1
		Total	36

At the conclusion of the computerized experimental task, industry participants completed a questionnaire designed to gather demographic data and assess manipulation of the independent variables. Included in this questionnaire (Appendix A) is a set of nine questions designed to test the participants' understanding of terms as defined for the decision task (e.g. Internal Rate of Return, Hurdle Rate, Operating Leverage, etc.). Incorrect responses to these questions indicate potential for misunderstanding or misusing the data attending the experimental choice tasks. Consequently, participants who incorrectly answered three or more questions were dropped from the data set. This procedure reduced the industry data set from 40 to 38 participants. Statistical inspection of the remaining 38 responses to the ISLab task discovered two participants displaying significant outlier qualities. Further inspection of their experimental responses and questionnaires revealed that these two participants did not respond to the experiment with serious intent and were, therefore, dropped from further analysis.

The mean age for the experienced capital budgeters is 37.4 years, and ranged from 23 to 58 years. Of the 36 participants, 34 are male and 2 are female. All but four of the participants have completed at least a bachelor's degree with courses in accounting and/or finance. The remaining four participants completed a bachelor's degree but were not clear as to the nature of their curriculum. Since the experiment task involved the use of a computer, participants responded to a self-report scale of computer experience. On a 1 to 10 scale (10 representing an individual with significant daily computer experience), the experienced participants' mean response was 7.4, indicating their general familiarity with working in a computer environment.

3.2.2 Novice participants. Undergraduate college students, majoring in accounting or finance, served as inexperienced capital budgeters. These students were solicited from upper-division accounting classes at a large Midwestern University. Students must have completed two courses containing instruction on capital budgeting techniques before participating in this study. Responses on the student questionnaire (Appendix B) indicated that this group, though educated in principles of capital budgeting, has no capital budgeting experience. Testing on this sample group took place over a period of three days.

Fifty-five students participated in the experiment. Of this number, four were excluded from the sample after incorrectly responding to three or more questions on the student questionnaire testing capital budgeting knowledge. Similar to the approach used in the experienced participant group, statistical analysis, followed by perusal of questionnaires, resulted in two more student participants being dropped as a result of a lack of serious intent in the ISLab task set. A final participant responded to the questionnaire as having had some capital budgeting experience and was, therefore, dropped from the study. Therefore, a total of 48 students served as inexperienced capital budgeters in this study.

The mean age in the group of student participants is 21.3 years. Of the 48 students used in this study, 20 are female and 28 are male. Subsequent analysis revealed no systematic gender effects within this group (discussed in Section 4.2.3).

On a 1 to 10 scale (10 representing an individual with significant daily computer experience), the inexperienced participants' mean response was 5.9. A two-sample t test reveals that this mean response is significantly different from the experienced participants' mean response of 7.4 ($p = 0.0009$). Since this experiment is established within a computerized environment, this fact presents a potential concern. However, ISLab was purposely designed and pretested to interface with users with little or no computer ability. Post-test questionnaires gave participants an opportunity to express concerns or problems in working with ISLab. No serious concerns were listed by participants from either group.

3.2.3 Task incentive. Students were paid $2.00 to complete the experiment. In addition, monetary incentives were used to motivate these novice participants by rewarding choices in concert with the decisions made by the more experienced participants. Since feedback effects are not of interest, all performance rewards were paid at the conclusion of the experiment. The anticipation of an overall monetary reward served as motivation for students to exert realistic effort in the capital investment choice task. The additional payment to students based on task performance ranged from $0.00 to $6.60 with a mean of $1.99. Promised feedback on experiment results, useful for company development of accounting information systems, provided incentive for experienced participants to exert serious effort in the experimental task. Other than the exceptions previously noted (two experienced and two student participants), responses on the questionnaire and subsequent interest in results of the experiment indicate that all participants were motivated in experimental performance.

On a scale of 1 to 5, each participant was asked to give his or her perception of the realism of the ISLab decision task (1 is Very Low and 5 is Very High). The mean response from industry participants was 3.7. The mean response from student participants was 3.5. Based on this information, coupled with post-experiment discussions with several participants, it is assumed that both subject groups were attentive to the ISLab tasks.

3.3 Task

Participants were presented with a series of six decision tasks each composed of a set of potential capital investments (alternatives). The participants chose the investment from among each set of alternatives they believed would make the largest contribution to company profitability. Each decision task consists of either 3, 5, or 7 alternatives. Each alternative within the set is consistently defined over 3, 5, or 7 attending information items (dimensions). These dimensions include both quantitative items (e.g. net present value) and qualitative items (e.g. estimation uncertainty). Thus, the construct, Information Load, is manipulated as a participant moves through a randomized order of decision tasks. Each decision task may have as few as nine information cues (3 alternatives x 3 dimensions) or as many as 49 information cues (7 alternatives x 7 dimensions).

3.3.1 Dimensions. The dimensions used to describe capital investment alternatives were developed with three qualities in mind. First, dimensions must be both realistic and viable to capital budgeting experts in making similar investment decisions. This was accomplished through discussions and pretesting with experienced capital budgeters outside of the study's sample set, review of several participating companies' capital budgeting manuals and use of industrial surveys utilized in previous research (see, for example, Bierman, 1986; Ferreira and Brooks, 1988; Pike and Sharp, 1989).

Second, the dimension values attending each decision task were chosen to insure that no clearly dominant choice alternative existed. That is, in a normative sense, participants were not expected to converge to a single alternative selection. No single alternative dominance allows examining information search strategies in a complex setting. Choice tasks containing a clearly dominant alternative do not encourage the careful and intensive information examination, representative of realistic capital budgeting decision tasks. To present a complex setting, two techniques were used. First, as described above, each alternative was designed to be non-dominant on any one dimension while being at least equal to other alternatives on all remaining dimensions. Second, each investment task was examined in its entirety by an independent experienced capital budgeter. The experienced subject concluded that no clearly dominant alternative existed.

Finally, dimensions were used that can be combined and segregated by a DSS applicable to this type of choice task. The DSS must strike a balance between presenting a complete set of relevant and detailed information and the potential to introduce possible confounding effects such as information overload (Gordon and Pinches, 1984). Essentially, this balance can become a question of information synthesis. For example, the net present value calculation is a single sum, yet this information cue can be segregated into several underlying information items such as the project's (1) discount rate, (2) expected life, (3) expected incremental cash flows and (4) investment cost.

To test for possible cognitive processing effects kindled by current and past information loads, the following general dimension set was used (in conjunction with the 3, 5 and 7 alternative sets) to manipulate Information Load: Net Present Value (NPV), Initial Cost and Risk. For the 3 dimension task, values for each of these three dimensions were presented to the decision maker. For the 5 dimension task, either NPV or Risk were replaced by three related information items. NPV was replaced by the Internal Rate of Return (IRR), Hurdle Rate and Annual Net Cash Flow. Risk was replaced by Payback, Estimation Uncertainty and Operating Leverage. Specific definitions for these dimensions were given in the participant's instructions found in Appendix A and Appendix B. For the 7 dimension task, both NPV and Risk was replaced. Table 3.2 summarizes the three possible dimension levels.

Table 3.2

Outline of Dimensions Attending the 3, 5 and 7 Dimension-Level Tasks[3]

	3 Dimensions	5 Dimensions	-or-	7 Dimensions
Initial Cost[I]	X	X	X	X
NPV[II]	X		X	
Risk[VII]	X	X		
IRR[III]		X		X
Annual Net Cash Flow[IV]		X		X
Hurdle Rate[V]		X		X
Payback[VI]			X	X
Estimation Uncertainty[VII]			X	X
Operating Leverage[VII]			X	X

[I]Quantitative cue.	Range: $150,000 to $300,000 ($30,000 increments)
[II]Quantitative cue.	Range: $0 to $75,000 ($15,000 increments)
[III]Quantitative cue.	Range: 11.0% to 19.0% (2.0% increments)
[IV]Quantitative cue.	Range: $30,000 to $50,000 ($5,000 increments)
[V]Quantitative cue.	Range: 9.0% to 17.0% (2.0% increments)
[VI]Quantitative cue.	Range: 4 years to 6 years (0.5 year increments)
[VII]Qualitative cue.	Range: Very Low to Very High (Likert-type scale below:)

(1) Very Low, (2) Low, (3) Average, (4) High, (5) Very High

3.3.2 Task procedure. Figure 3.2 is a diagram describing the flow of an ISLab session. An example of the main screen presented to the participant with seven alternatives, each alternative defined over seven dimensions (or attributes), is seen in Figure 3.3.

[3]One dimension obviously missing from this list is each investment's expected life. Since these investments are mutually exclusive, there is a need to compare projects over the same time period. In order to avoid assumptions such as the possibility of replacing short-lived investments with equivalent projects (Gordon and Pinches, 1984), all projects are assumed to last for 10 years with immaterial salvage values.

Figure 3.2

ISLab System Flow Diagram

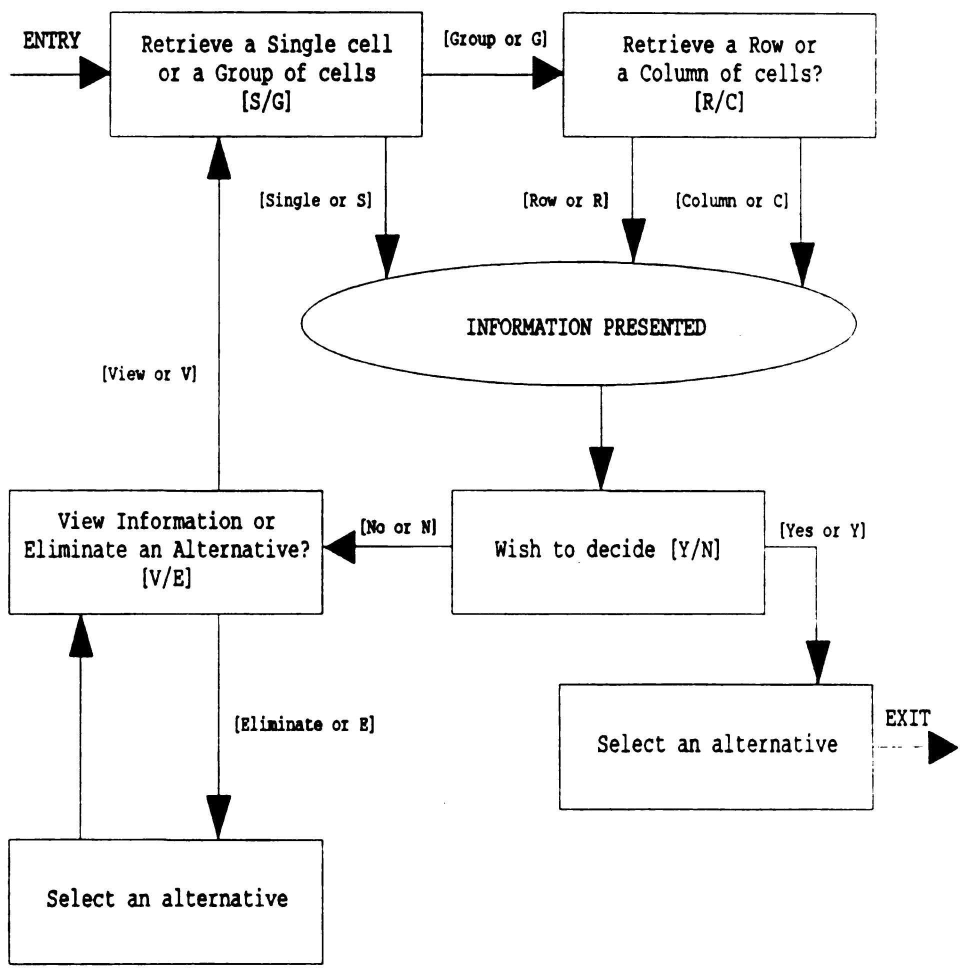


Figure 3.3

ISLab Initial Main Screen

```
Altern-   Dimensions
atives    1  2  3  4  5  6  7
-------   --------------------
  A-      -  -  -  -  -  -  -
  B-      -  -  -  -  -  -  -
  C-      -  -  -  -  -  -  -
  D-      -  -  -  -  -  -  -
  E-      -  -  -  -  -  -  -
  F-      -  -  -  -  -  -  -
  G-      -  -  -  -  -  -  -

                                                Dimension Key
                                                -------------
                                                1- IRR
                                                2- Annual Cash Flow
 Single Cell or Group of Cells (S/G):           3- Hurdle Rate
                                                4- Cost
                                                5- Payback
                                                6- Estimation Uncertainty
        (Escape Key is available)               7- Operating Leverage
```

After completing desired training (described in section 3.4.1), the participant initiates the first ISLab experimental task. The program first requires the participant to choose a view of either 1) a single dimension for a single alternative **[Single Cell or S]** or 2) all information for a group of alternatives or dimensions **[Group or G]**. If the participant chooses to view an information group **[G]**, the program presents a prompt to view either information for a set of alternatives **[Row or R]** or for a set of dimensions **[Column or C]**. ISLab then prompts for the letter of the alternative and/or the number of the dimension (or attribute) desired. The information for the alternative(s) and dimension(s) desired is displayed. For example, if the participant wants to view information on internal rate of return (IRR) for all alternatives, he or she would chose the group **[G]** option, then select columns **[C]** and enter 1. The requested information would then be presented as seen in Figure 3.4.

Figure 3.4

ISLab Main Screen After Requesting Information from Column 1

```
Altern-   Dimensions
atives    1  2  3  4  5  6  7                 IRR
-------   ---------------------               ---------
  A-      *  -  -  -  -  -  -                 A:  11%
  B-      *  -  -  -  -  -  -                 B:  13%
  C-      *  -  -  -  -  -  -                 C:  15%
  D-      *  -  -  -  -  -  -                 D:  13%
  E-      *  -  -  -  -  -  -                 E:  11%
  F-      *  -  -  -  -  -  -                 F:  19%
  G-      *  -  -  -  -  -  -                 G:  17%

                                              Dimension Key
                                              -------------
                                              1- IRR
                                              2- Annual Cash Flow
                                              3- Hurdle Rate
                                              4- Cost
      Wish to decide? (Y/N):                  5- Payback
                                              6- Estimation Uncertainty
                                              7- Operating Leverage
```

After viewing the requested information, the participant has the option of selecting the desired alternative or requesting more data **[Wish to decide? (Y/N)]**.

If prepared to make a decision, the participant is prompted to enter the letter of the desired alternative, then ISLab moves the participant on to the next decision task. If not ready to decide, the participant chooses to either retrieve additional data **[View Information or V]** or eliminate undesirable alternatives **[Eliminate Alternatives or E]**. Eliminated alternatives are removed from further consideration on both the main and summary screens and can not be retrieved again. (When specifically asked, participants reported no problems with erroneous eliminations.) Choosing V returns the participant back to the beginning of the procedure.

3.3.3 Pretests. Novice and experienced individuals were employed in extensive development and pretesting of realistic decision tasks and viable manipulations of experimental variables. Two separate groups of students (group sizes of 19 and 10, respectively) were used initially to pretest the ISLab decision tasks. Manipulation of information loads (i.e. varying the number of alternatives and dimensions) were evaluated to ensure movement in the resulting information search strategies. Additionally, system characteristics were remodeled or added to enhance the subject's ability to move about in the ISLab computerized environment comfortably while completing the decision tasks.

After pretesting with student subjects, the ISLab instrument was pretested on a small group of four industry subjects. This pretest resulted in one major adaption in the ISLab tool, which provided significant enhancement of the system's mental process tracing ability. Inspection of the industry pretest sample provided anecdotal evidence that experience effects may be present in capital budgeting. As a final check before actual experimentation began, the ISLab instrument was pretested on one final group of 12 students. Based on this final pretest, users interfaced comfortably with the ISLab program while exhibiting noticeable variance in their information search strategy as ISLab manipulated levels of alternatives and dimensions.

3.4 Instrument

ISLab is an adaptation of a computerized instrument of the same name previously developed by Cook (1987). Consistent with the traditional three-part DSS paradigm (Turban, 1990), ISLab is composed of three modules: the model management, user-interface and data management subsystems. These modules interact to present explicitly a series of decision tasks to the experimental participant while unobtrusively recording all information search activity. ISLab is designed to run on IBM and compatible PCs with one disk drive. Either a color or monochrome monitor may be used. The system resides on a single 5 1/4" or 3 1/2" floppy disk. Only the standard operating system software must be loaded on the PC prior to running ISLab.

3.4.1 Model management subsystem. The model management subsystem allows the researcher to create and manipulate decision models for the user-interface subsystem. Both quantitative and qualitative information is used to define any number of decision alternatives across a variety of attending dimensions. Hence, ISLab is easily adapted to explore variables and constructs outside of those evaluated in the current study.

3.4.2 User-interface subsystem. The user-interface subsystem is divided into two distinct sessions. Initially the participant is trained by watching an automatic demonstration presented by ISLab. The automatic demonstration presents a typical decision task and moves randomly through a series of information requests, demonstrating all ISLab features. Following the automatic demonstration, a sample decision problem is presented so participants may practice requesting data items and selecting an alternative. Both the automatic demonstration and the sample decision problem can be repeated as many times as desired. When the participant is comfortable with the system, the participant then initiates the second stage of the experiment. This second stage is a random order of experimental decision tasks varied in line with the theories tested in this study.

3.4.3 Data management subsystem. Three output files, unobserved by participants in the experiment, are created by the data management subsystem for analysis. The first consists of miscellaneous information used to identify the particular experimental session and the participant as well as information concerning the participant's training sessions. The second file contains parameters describing each experimental decision task explored by the participant. These parameters include each task's number of alternatives and the number of dimensions per alternative, the amount of information searched and the participant's final decision. The third file consists of the decision stream, i.e., the matrix addresses of the data items examined and the beginning point of inspection time for each data item (see Figure 3.5).

Figure 3.5

ISLab Sample Output Listing

```
05-21-1991
John Doe
State University
Automatic Demonstration Runs: 1          End Time 00:03:30
Hands-on Practice Runs: 1                End Time 00:06:16
Practice Alternatives Eliminated: 1
------------------------------------------------------------
Beginning of Decision 1
Experimental Task 4
Size: 7 Alternatives and 7 Dimensions
Decision Stream:              ELEMENT    TIME
(*indicates an elimination)   -------    --------
                              A3         00:07:07
                              B3         00:07:08
                              C3         00:07:08
                              D3         00:07:08
                              E3         00:07:08
                              F3         00:07:08
                              G3         00:07:08
                              *D         00:07:18
                              A7         00:07:33
                              B7         00:07:33
                              C7         00:07:33
                              E7         00:07:33
                              F7         00:07:33
                              G7         00:07:33
                              *A         00:07:52
                              *C         00:07:55
                              B6         00:08:19
                              E6         00:08:19
                              F6         00:08:19
                              G6         00:08:19
                              B2         00:08:37
                              E2         00:08:37
                              F2         00:08:37
                              G2         00:08:37
                              G1         00:08:51
                              G2         00:08:51
                              G3         00:08:51
                              G4         00:08:51
                              G5         00:08:51
                              G6         00:08:51
                              G7         00:08:51

  CHOICE: G     TIME 00:09:16
  NUMBER OF ALTERNATIVES ELIMINATED: 3
  STATISTICS:
  1.          Proportion Searched:  .4897959
  2.  Variability by Alternatives:  .2629408
  3.    Variability by Dimensions:  .3315934
  4.          Direction of Search: -.7

  End of Decision 1
```

Using the three output files, the data management subsystem generates a report listing all queries, eliminated alternatives and alternative chosen for each matrix along with elapsed times. In addition, four measures are calculated for each matrix: the proportion of information searched, the variability in the proportion of information searched by alternatives, the variability in the proportion of information searched by dimensions and the direction of the search (either an interdimensional or an intradimensional search). As discussed in section 2.3, these four measures are indicators of the type of information search strategy employed by the experimental participant (Cook, 1987; Klayman, 1983; Payne, 1976). The specific calculations for these four metrics are presented in section 3.4.4. A sample output listing for a single decision task is presented in Figure 3.5. As a point of reference, Figure 3.6 displays all the cells inspected in the information search strategy displayed in the output listing from Figure 3.5.

Figure 3.6

Sample Information Search Pattern

Altern-atives	Dimensions 1	2	3	4	5	6	7
A-	-	-	*	-	-	-	*
B-	-	*	*	-	-	*	*
C-	-	-	*	-	-	-	*
D-	-	-	*	-	-	-	-
E-	-	*	*	-	-	*	*
F-	-	*	*	-	-	*	*
G-	*	*	*	*	*	*	*

* indicates an examined cell

3.4.4 Mathematical indicators of Information Search Strategy. An important part of the output created by ISLab is the automatic generation of the four measures that serve as indicators for the dependent variable Information Search Strategy. Using the decision stream presented in Figure 3.5 and Figure 3.6 as an example, these four quantities, described as indicators of specific information search models in Table 2.2 in the previous chapter, are mathematically defined below (Klayman, 1983; Cook, 1987):

1. Proportion Searched (Prop Search): Measured as the number of cells examined divided by the total number of cells.

   e.g., Prop Search = 24/49 = .49

2. Variability in Proportion Searched Across Alternatives (Varib By Alts): Measured as the population standard deviation of the proportion searched per alternative across the set of available alternatives.

3. Variability in Proportion Searched Across Dimensions (Varib By Dims): Measured as the population standard deviation of the proportion searched per dimension across the set of available dimensions.

   Varib By Dims (Alts) is directly measured as

$$[((\Sigma x_i^2 - (\Sigma x_i)^2/n)/n]^{\frac{1}{2}}$$

   where n = number of total dimensions (alternatives) and x_i = proportion of dimension (alternative) i searched.

   e.g., Varib by Alts = $[(2.16 - (11.76/7))/7]^{1/2} = .26$

   e.g., Varib by Dims = $[(2.45 - (11.76/7))/7]^{1/2} = .33$

4. Search Direction: Measured as

   (Inter-Intra)/Inter+Intra)

   where Intra is the number of instances in which the nth+1 item searched is of the same dimension as the nth and Inter is the number in which the nth+1 is of the same alternative as the nth. A score of 1.0 represents a strict interdimensional search and a score of -1.0 represents a strict intradimensional search. Similar to above statistics, cell previously viewed are not counted again in the calculation.

   e.g., Search Direction = (3 - 17)/(3 + 17) = -.70

These four measures are used to test the three proposed hypotheses described in Section 3.3.

3.4.5 <u>Manipulation checks</u>. As a manipulation check on the independent variable Information Load, the ISLab program records the amount of time spent deliberating each choice task. For example, a significant increase in time spent on the 3x7 task compared to the 3x3 task indicates the effective increase of information load on the participant's decision process. Additional manipulation checks to ensure the participants' understanding of dimensions utilized and his or her level of experience were included as questions on the post-test survey (Appendix A). Some attempt to check the effect of the constructs Previous Search Strategy and Previous Information Load was also included via questions on the post-test survey. However, individual's inability to introspect their own mental processes (Stahl and Zimmerer, 1984) makes the manipulation difficult to check.

3.4.6 Traditional process tracing tools. To develop an accurate map of the mental process associated with capital budgeting is a difficult task. In cognitive psychological research, several types of process-tracing techniques have been used in developing insight into the internal decision process. However, in this particular decision domain, capital budgeting, ISLab provides some advantages over traditional process tracing methods.

Libby (1981) recounts five methodological problems with traditional process-tracing techniques such as information boards, verbal protocols and eye movement recordings. Each of these techniques suffers from at least some of the following problems: (1) Participants must access possibly inaccessible higher-order cognitive processes. (2) The nature of the process-tracing technique may obtrude and possibly alter behavior. (3) The objectivity of data-coding methods is questionable. (4) Small sample sizes result in indistinguishable systematic and random components of behavior. (5) The sheer volume of data present tremendous aggregation and communication challenges when relating the results to readers.

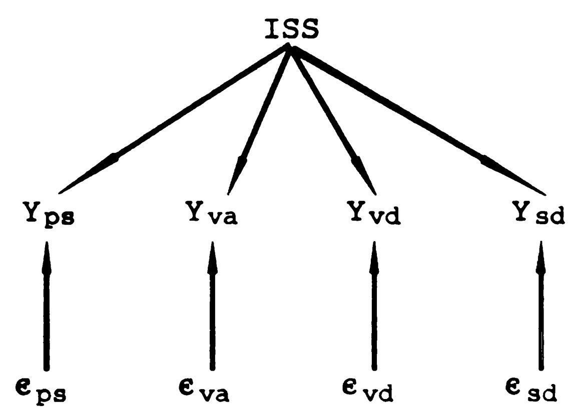
Like other process tracing techniques, ISLab is not a perfect methodology. No technique is without weakness in the difficult task of generating insight into human cognitive processes. Yet in response to the deficiencies outlined by Libby, ISLab automatically traces the information search while providing a relatively natural capital investment decision environment. The participant should be able to concentrate on the task at hand without being distracted by the presence of a researcher or observer, since the researcher does not need to take an active part in the experimental session. Additionally, ISLab easily obtains an historical trace of a participant's information search process in the form of the four objective metrics described above. This standardized approach to mental process tracing allows much larger sample sizes as compared to traditional approaches.

3.5 Method of Analysis

3.5.1 Confirmatory factor analysis. Before directly testing each hypothesis, initial evaluations were made on the viability of the four indicators of Information Search Strategy -- Prop Search, Varib By Alts, Varib By Dims and Search Direction. Confirmatory factor analysis was used in this initial evaluation. Figure 3.7 presents the confirmatory factor model based on theory in research previously reviewed (Klayman, 1983; Biggs et al., 1985; Cook, 1987).

Figure 3.7

The Information Search Strategy Factor Measurement Model



where
ISS = the unobserved information search strategy factor,
Y_x = the observed variable Prop Search, Varib By Alts, Varib By Dims, and Search Direction, respectively and
ϵ_x = the unobserved error term for Prop Search, Varib By Alts, Varib By Dims and Search Direction, respectively.

Fink and Monge (1985) note that confirmatory factor analysis, like traditional statistical models such as multiple regression, analysis of variance and canonical correlation analysis, is a technique which assumes that variables are related by equations linear in parameters, i.e., "that a dependent variable may be decomposed into a linear weighted sum of predictors, plus an (unobserved) error" (p. 170). If the relationship between the observed variables (Ys) and the ISS factor is linear, then Figure 3.7 can be translated into a general linear regression equation:

$$Y_x = \lambda_x ISS + \epsilon_x$$

where:

λ_x = the slope (or "loading" in factor analysis parlance) of variable Y_x onto ISS and
ϵ_x = the error in the regression of Y_x on ISS (Hunter and Gerbing, 1982).

If the four observed variables measure the same factor, Information Search Strategy (ISS), then the observed variables are said to form a unidimensional measure. Evaluating the content validity of such a measurement model requires that observed correlations between variables satisfy a "product rule for internal and external consistency" (Hunter and Gerbing, 1982). For example, in evaluating internal consistency, the following relationship must hold (the product rule of internal consistency):

$$r_{Yva,Yvd} = (r_{Yva,ISS})(r_{Yvd,ISS})$$

where $r_{x,y}$ = correlation between either two indicators of the same factor or between an indicator and an outside factor.

Thus, the correlation between Varib By Alts and Varib By Dims should be a product of their factor loadings on the unobserved ISS trait. This relationship should be evident in Figure 3.7. To test for internal consistency, the parameters $r_{Yx,ISS}$ are estimated from the data. Then the product rule of internal consistency is used to reproduce the inter-item correlations. The reproduced correlation matrix must estimate the observed correlation matrix to within sampling error, else the four observed variables cannot be considered internally consistent.

The second test of unidimensionality, external consistency, is satisfied via evaluation of the measurement model's parallelism with external factors. The notion of internal consistency specifies how items composing a unidimensional cluster should correlate with one another. Similarly, external consistency (or parallelism) specifies how these same items should correlate with variables outside the cluster (Hunter and Gerbing, 1982). Specifically, items within a unidimensional measurement model should follow a "product rule of external consistency" with outside factors. For instance,

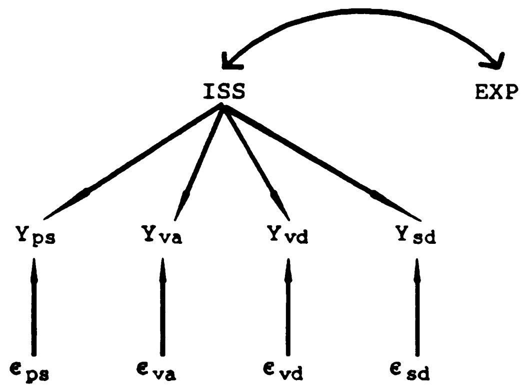
$$r_{Yva,EXP} = (r_{Yva,ISS})(r_{ISS,EXP})$$

where EXP = a dichotomous variable representing the participants' level of experience.

This relationship states (as manifested by the path diagram in Figure 3.8) that the correlation between Varib By Alts and EXP is a product of the Varib By Alts factor loading on ISS and the correlation between ISS and EXP. To test for external consistency, the same general procedures applicable to tests of internal consistency are followed. A factor correlation matrix for the ISS factor and observed items external to the ISS factor is estimated from the data. For this study, external items evaluated are EXP (defined above), ORDER (the order number for each of the six choice tasks) and TASK (the identification of each of the six choice tasks). If the measurement model is externally consistent, the product rule of external consistency must predict the factor correlation matrix to within sampling error.

Figure 3.8

The Relation between Information Search Strategy Measurement Model and Observed Experience



Once a unidimensional model of Information Search Strategy is established, the clustered items are standardized and summed to furnish an objective score for ISS usable in traditional statistical analysis. Variables with a mean = μ_X and a standard deviation = σ_X are standardized with the following equation

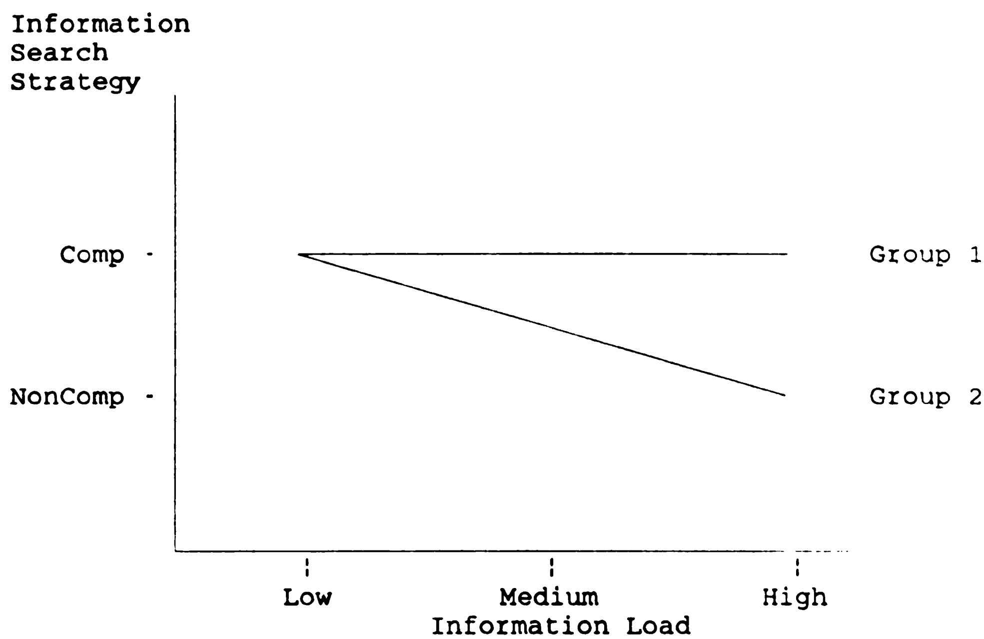
$$(X - \mu_X)/\sigma_X$$

3.5.2 ANOVA. After factor analysis confirms the linear relationship of the observed variables and the variables are standardized and summed, ANOVA is used to evaluate H_1 and H_3. As described in section 3.1, this analysis follows a 2 x 3 x (3) design on factors E (Experience), A (Alternatives) and D (Dimensions), respectively, with repeated measures on the D factor. To evaluate **H_1**, concurrent levels of alternatives and dimensions are used. To evaluate **H_3**, the levels of alternatives and dimensions used in the prior choice task are analyzed. To test directly for specific interactions of experience with information load, contrast coding (Rosenthal and Rosnow, 1985) is utilized. This approach allows for greater statistical power than conventional ANOVA without increasing Type 1 error rates (Buckless and Ravenscroft, 1990). Such an approach is justified since the functional form of the relationship between Information Load and Information Search Strategy is specified, *a priori*.

Specifically, previous research (discussed in sections 3.1 and 3.2) proposes the relationship depicted in Figure 3.9.

Figure 3.9

Graph of Ordinal Interaction



Previous research is unclear on whether it is experienced or inexperienced decision makers who tend to remain compensatory as information load is increased. **H_1** proposes that concurrent levels of information attending the decision task and decision maker experience interact. If the nature of this interaction is that experienced capital budgeters remain relatively compensatory compared inexperienced capital budgeters, then experienced capital budgeters display a search strategy similar to Group 1 in Figure 3.9

and inexperienced capital budgeters are similar to Group 2. If the interaction results from inexperienced capital budgeters remaining relatively compensatory, these individuals respond similar to Group 1 and experienced capital budgeters are comparable to Group 2. Contrast coding allows testing of these particular *a priori* relationships. Therefore, the analysis of variance used to examine H_1 and H_3 is refined in this manner.

Essentially, this E x A x (D) design represents a combination of two simpler experiments, one with two independent group factors (factors E and A) and the other with repeated measures (factor D) (Keppel, 1982). The use of repeated measures allows isolation of the variance due to individual differences across subjects and then excludes that variance from the denominator of the F-ratio. This ability to isolate within-subject "noise" greatly enhances the power of the F-test to determine statistical significance achieved. However, the strict use of repeated measures has recently come under question (Harsha and Knapp, 1990). The concern for sensitization or "demand" effects has caused some researchers to challenge rigid repeated measures studies (Pany and Reckers, 1987). The manipulation of level of alternatives as an independent groups factor is an effort to control for demand (as well as fatigue) effects. To guard against possible bias of statistical significance for the dimensions manipulation, a strength of association statistic (ω^2) is used. Essentially, ω^2 is a conservative estimate of the proportion of variance in a dependent variable measure that is explained or accounted for by an independent variable or interaction effect (Harsha and Knapp, 1990).

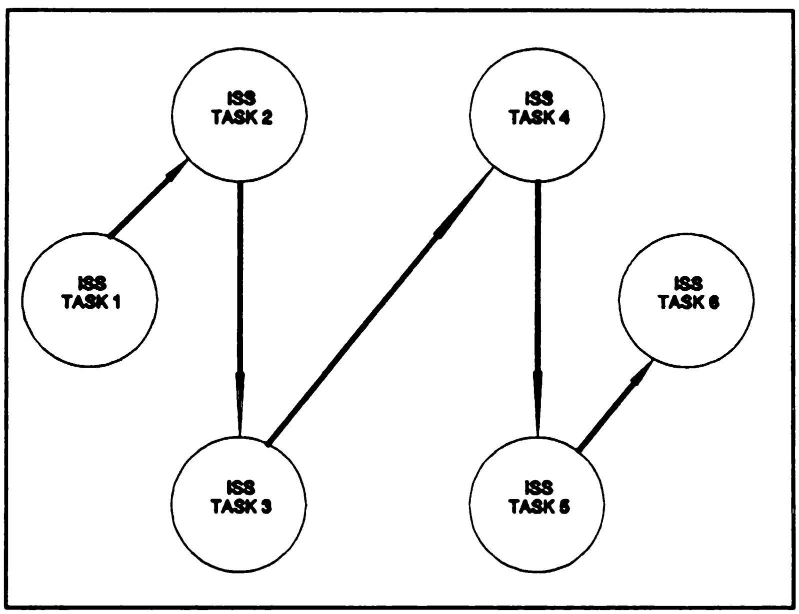
3.5.3 Path analysis. The remaining hypothesis, H_2, is tested using path analysis. Path analysis is an extension of multiple regression analysis in that it can aid in the interpretation of a multiple regression by showing both the direct, indirect and spurious effects of independent variables on the dependent variable (Lewis-Beck, 1974). It is this specific quality of path analysis that allows the building of causal models at a level of complexity unattainable by conventional multiple regression analysis (Christopher and Elliott, 1970).

To test for the hypothesized functional fixation relationship among observations of the latent variable Information Search Strategy, the two-step analysis technique recommended by Gerbing and Hunter (1981) is used. This strategy uses a centroid oblique multiple groups analysis for confirmatory factor analysis to test the measurement model (discussed in section 3.5.1). After a correct measurement model is established, the factor correlations are submitted to a single equation path analysis based on ordinary least squares. CFA, a specialized confirmatory factor analysis program created by Hunter and Hamilton

(1987), is used to confirm the measurement model. Following the two-step analysis approach, another specialized program, PATH (Hunter, 1985), is used to develop the path model parameters for statistical testing. The path analysis model initially used to evaluate H_2 is portrayed in Figure 3.10 as a simple causal chain pattern.

Figure 3.10

A Path Model Depicting Functional Fixation on Information Search Strategy (ISS)



Each arrow in the path model in Figure 3.10 is associated with a path coefficient. Every correlation between variables is predicted from a set of path coefficients using a product rule (Hunter and Gerbing, 1982). For example,

$$r_{ISS1,ISS3} = (p_{ISS1,ISS2})(p_{ISS2,ISS3})$$

where:

ISSn = the information search strategy observed in task n and
p = the corresponding path coefficient between two tasks.

The standard normal curve is employed to test for significant deviations between predicted and actual correlations. Insignificant residuals (differences between predicted and actual correlations) are evidence of a functional fixation phenomenon.

The subject pool is segregated based on experience level and the model proposed in Figure 3.10 is evaluated for each experience set. Significant size differences in path coefficients between experience levels indicate interaction of experience and functional fixation. When testing for significant differences in path coefficients, Hunter and Gerbing (1982) note that if each variable has a solitary causal antecedent (as depicted in Figure 3.10) then the path coefficient is statistically tested as a simple correlation. If there is multiple causation, then the path coefficients are standardized beta weights rather than simple correlations.

3.6 Summary

An outline of the experimental setting, participants, decision task, instrument, and investigative techniques used for the research questions are discussed in this chapter. The first section contains a general overview of the research design. The second section describes the two groups of participants used in this study and presents some descriptive data. Section three reviews the decision task design and describes validation of the task through pretesting efforts. The instrument utilized to gather observations on the two groups of participants (ISLab) is presented in the fourth section. Additionally, the mathematical indicators of an information search strategy are presented and ISLab is contrasted with more traditional process tracing tools.

In the final section of this chapter, three facets of the statistical analysis are presented. First, confirmatory factor analysis is presented to develop an appropriate measure of information search strategy. Second, ANOVA and contrast coding are discussed as the means of evaluating H_1 and H_3 -- effects of information load attending current and past capital investment choice tasks, respectively. Third, path analysis is used to model functional fixation on previous information search strategy measures and test H_2. The experimental results analyses follow in the next chapter.

CHAPTER IV

DATA ANALYSIS

4.0 Overview

This chapter contains the experimental results. As discussed previously, the experiment was conducted in two stages. First, a set of experienced capital budgeters performed the ISLab capital budgeting task set. Then a group of students (i.e. inexperienced capital budgeters) performed the ISLab capital budgeting task set. The purpose is to test for effects of information load, data fixation, and functional fixation on the information search strategy. More importantly, the interaction of experience with the effects listed above was specifically analyzed.

Before hypotheses testing, four indicators of information search strategy are investigated for unidimensional factor loadings on a single latent variable. The first section of the chapter reports the results of this confirmatory factor analysis. Section 2 describes the results of manipulation checks on the independent variable, Information Load, and presents analysis for potential training, fatigue and gender effects. ANOVA results testing Hypothesis 1, information load effects, are presented in the third section. The fourth section describes ANOVA results for Hypothesis 2, data fixation effects. In section 5, Hypothesis 3, functional fixation effects, is examined using path analysis. The final section of this chapter is a summary of the overall results.

4.1 Confirmatory Factor Analysis

4.1.1 Internal Consistency. Initially, all four indicators of the latent factor, Information Search Strategy (ISS), are tested for unidimensional fit. These four indicators are Proportion Searched (PS), Variability in Proportion Searched across Alternatives (VA), Variability in Proportion Searched across Dimensions (VD), and Search Direction (SD). These four indicators combine to form an over-identified model allowing testing of model fit (Hunter and Gerbing, 1982). Table 4.1 presents the correlation matrix for the four ISS indicators and their individual factor loadings on the ISS factor using ordinary least squares (OLS) techniques.

The observed factor loadings and inter-item correlations are seen in the first two panels, respectively, of Table 4.1. The Predicted Correlation Matrix panel is obtained by the product rule of internal consistency discussed in Section 3.5.1. Each predicted correlation between items is the product of the items' individual load on ISS. For example,

$$\mathbf{r}_{Yva,Yvd} = .38 = (.45)(.85) = (\mathbf{r}_{Yva,ISS})(\mathbf{r}_{Yvd,ISS})$$

Table 4.1

Internal Consistency Among PS, VA, VD and SD

(n = 504)

Factor Loadings on Information Search Strategy (ISS)

	PS	VA	VD	SD
ISS Factor	1.04	.45	.85	.48

Observed Correlation Matrix

	PS	VA	VD
VA	.54		
VD	.91	.29	
SD	.42	.23	.47

Predicted Correlation Matrix
Using the Factor Loadings

	PS	VA	VD
VA	.47		
VD	.88	.38	
SD	.50	.22	.41

Error Matrix (Observed - Predicted)

	PS	VA	VD
VA	.07*		
VD	.03***	.09*	
SD	.08*	.01	.06

Overall Chi-Square on Error Matrix = 12.096

* $p < .10$
** $p < .05$
*** $p < .01$

The Error Matrix contains the difference between each observed correlation and its respective predicted correlation. These residuals are evaluated for significance in size using a two-tailed t-test based on n = 504 (84 total participants * 6 task observations per participant). Overall, the total matrix is examined for significance using a chi-square test. However, individual evaluation of each residual provides a stronger test of significant deviation from the posited model (Hunter and Gerbing, 1982). This approach, focusing on individual residual evaluation, is maintained throughout remaining analyses. As seen in the last panel of Table 4.1, one of the six residuals is significant in size. Additionally, three residuals are marginally significant. Therefore, the measurement model presented in Figure 3.6 may not be internally consistent.

4.1.2 <u>External Consistency</u>. Better insight into the posited measurement model of Information Search Strategy is obtained as the content validity analysis continues via external consistency testing. Table 4.2 illustrates analysis for consistency of the four proposed ISS indicators with three external factors: 1) the experience level of each participant (EXP), 2) the order of each participant's set of choice tasks (ORDER) and 3) the identification of each of the six choice tasks (TASK).

Table 4.2

External Consistency of PS, VA, VD and SD with EXP, ORDER and TASK

(n = 504)

ISS Factor Correlations with External Items

	EXP	ORDER	TASK
ISS Factor	.11	.03	.08

Observed Correlation Matrix

	PS	VA	VD	SD
EXP	.05	.08	.02	.15
ORDER	.04	.05	.00	-.01
TASK	.12	.05	.12	-.06

Predicted Correlation Matrix

	PS	VA	VD	SD
EXP	.11	.05	.09	.05
ORDER	.03	.01	.03	.01
TASK	.08	.04	.07	.04

Error Matrix (Observed - Predicted)

	PS	VA	VD	SD
EXP	-.06	.03	-.07	.10*
ORDER	.01	.04	-.03	-.02
TASK	.04	.01	.05	-.10*

* $p < .10$
** $p < .05$
*** $p < .01$

The observed correlations between the ISS factor (computed as the sum of the four standardized indicators PS, VA, VD and SD) and the three external items EXP, ORDER and TASK, are seen in first panel of Table 4.2. The second panel contains the observed correlations between the ISS indicators and the three external items. Each indicator's relationship with items external to the ISS measurement model should parallel that indicator's factor load on ISS (as seen in Table 4.1) and the correlation of the ISS factor and the external item. This relationship, previously discussed in Chapter III, is seen in Figure 3.7. Therefore, the third panel, containing the Predicted Correlation Matrix, is developed using the product rule of external consistency. For example,

$$\mathbf{r}_{Yva,EXP} = .05 = (.45)(.11) = (\mathbf{r}_{Yva,ISS})(\mathbf{r}_{ISS,EXP})$$

where $\mathbf{r}_{Yva,ISS}$ is the VA factor loading seen in the first panel of Table 4.1

The Error Matrix in the fourth panel of Table 4.2 contains the difference between each observed correlation and its respective predicted correlation. As seen, the SD indicator is inconsistent in its relationships with two of the three external factors (EXP and TASK). Therefore, the ISS measurement model based on the four indicators PS, VA, VD and SD may not be not externally consistent. This, coupled with questionable internal consistency, casts serious doubt as to the model's content validity. The reliability of this model (coefficient alpha) is established as .78.

Returning to the theoretical relationships among the four ISS indicators (see Table 2.2 from Chapter II), the source of the model's inconsistency can be understood. In general, the direction of information search (SD) employed by the decision maker emerges as an ambiguous discriminator between compensatory and noncompensatory information search strategy models. Direction of search may be either interdimensional or intradimensional within both the compensatory and the noncompensatory general model. Evidence of this ambiguity is seen in the external consistency analysis, revealing that the relationship of SD with the examined external factors is not in concert with the three remaining indicators. Hence, based on both theoretical and analytical evidence, the SD indicator was dropped and the ISS measurement model was reanalyzed using just PS, VA and VD.

A measurement model defined over four indicators provides six inter-item correlations of which four are parameters defined by the model. Therefore, the model is over-identified. The two remaining unconstrained correlations provide testable parameters for evaluating internal consistency (Hunter and Gerbing, 1982). However, a measurement model defined over three indicators provides only three correlations, all of which are delineated by the model. This type of model is just-identified and, therefore, is not subject to evaluation since no testable relationships exist not constrained by the model. Therefore, the ISS measurement model containing only PS, VA and VD conforms to the product rule of internal consistency by definition. However, this new model is still evaluated for external consistency, allowing some judgment of content validity. The external consistency analysis for the ISS measurement model containing only PS, VA and VD is presented in Table 4.3.

Table 4.3

External Consistency of PS, VA and VD with EXP, ORDER and TASK

(n = 504)

Factor Loadings on ISS

	PS	VA	VD
ISS Factor	1.16	.44	.77

ISS Factor Correlations with External Items

	EXP	ORDER	TASK
ISS Factor	.06	.04	.12

Predicted Correlation Matrix

	PS	VA	VD
EXP	.07	.03	.05
ORDER	.05	.02	.03
TASK	.14	.05	.09

Error Matrix (Observed - Predicted)

	PS	VA	VD
EXP	-.02	.05	-.03
ORDER	-.01	.03	-.03
TASK	-.02	.00	.03

* $p < .10$
** $p < .05$
*** $p < .01$

The first panel of Table 4.3 presents the factor loadings based on OLS techniques for this new ISS measurement model composed of PS, VA and VD. The large difference between the VA and the VD factor loadings is evidence of the density effect discussed in Section 2.4.3. Correlations of this new measure of ISS (the sum of the standardized PS, VA and VD measures) with the external factors EXP, ORDER and TASK are displayed in the second panel. As done in Table 4.2, the measurements contained in the first two panels of Table 4.3 are combined to form the Predicted Correlation Matrix found in the third panel. Differences between the predicted correlations and the observed correlations (taken from the second panel of Table 4.2) form the Error Matrix displayed in the fourth panel of Table 4.3.

All residuals in the Error Matrix are insignificant in size. Therefore, the three-indicator model of ISS displays content validity. Additionally, the reliability of this new model (coefficient alpha) increases to .81 (reliability is .78 for the four-indicator model). Based on the above analysis, the three-indicator (Percent Searched, Variability by Alternative and Variability by Dimension) measurement model of Information Search Strategy is used in the remaining evaluation of the test hypotheses.

4.2 Manipulation Check and Extraneous Effects

4.2.1 Manipulation check. The information load attending each capital budgeting decision was manipulated by varying the level of alternatives (three, five or seven) and the level of dimensions (three, five or seven). Therefore, participants experienced information load ranging from a low of nine cues (three alternatives by three dimensions) to a high of 49 cues (seven alternatives by seven dimensions). The effect of these various levels of information load were then analyzed for impact on current and subsequent search strategies.

It is important to evaluate the effectiveness of the information load variable manipulation. One approach considered was to ask participants at the conclusion of each choice tasks for their perspective of information load influence on their search strategy. However, since the experiment was partially a repeated-measures design, this approach is unnecessarily interruptive to the decision process.

One characteristic of ISLab is its ability to trace the information search processes without intruding into the decision stream (as compared to other traditional process-tracing methodologies). In concert with this characteristic, a similarly unobtrusive technique is used to check experimental manipulation of information load. Increased information load typically results in higher cognitive effort in the choice process. Increased cognitive effort is surrogated by an increase in total time spent in the decision process. The ISLab tool is programmed to track the total time elapsed from the point of initial presentation of the choice task screen (see Figure 3.3) until the participant selects the desired capital investment. The average decision spent at each information load level for all participants is reported in Table 4.4.

Table 4.4

Average Decision Time Spent in Minutes at Each Level of Information Load

(The standard deviation for each cell is in parentheses)

DIMENSIONS

ALTERNATIVES

	3 Dims	5 Dims	7 Dims
3 Alts.	2.56 (1.84)	3.75 (2.17)	4.26 (2.70)
5 Alts.	3.52 (1.64)	4.95 (3.16)	5.36 (3.16)
7 Alts.	4.25 (2.86)	4.80 (2.38)	5.78 (3.41)

As seen in Table 4.4, there is a consistent increase in time as the participants move from low to high levels of dimensions and alternatives. ANOVA results indicate that the main effect on decision time is significant for both the level of alternatives ($p = .001$) and the level of dimensions ($p = .000$). No significant interaction effect of alternatives and dimensions on decision time is observed ($p = .734$). However, linear relationships between information load and decision time is not clearly theorized in the literature. The current study posits that information load directly affects the decision *method*. Therefore, a second indicator of experimental manipulation was also employed.

Several open-ended questions on the post-test questionnaire (Appendices A and B) requested information from the participants on their perception of information effects and their consistency in applying a decision strategy. Of the 48 novice participants, 41 indicated that varying the information load had a perceived effect on the decision method. Of the 36 experienced participants, 32 indicated a perceived effect on decision method. Samples of participants' post-test comments on the information load manipulation are presented in Table 5.5. These responses, coupled with the trend of increasing decision time seen in Table 4.4, indicate an effective manipulation of the independent variable, Information Load.

Table 4.5

Sample Comments on the Information Load Manipulation

Novice Participants:

"The more information, the harder the decision."

"With less information, I used a row approach (versus columns) and evaluated all information."

"With many dimensions, I had to prioritize."

"I looked at a couple of different criteria for some decisions and zeroed in on one item in other decisions."

Experienced Participants:

"I experienced difficulty in approaching each decision in a consistent manner due to the varying amounts of information offered."

"More information made for a more difficult decision -- difficult to decide on elements to view."

"The more variables, the more likely I was to eliminate options on the basis of one variable and then choose among the remaining."

"The more information, the quicker I tried to eliminate some alternatives. I tried to narrow the field to a reasonable number of potential candidates."

4.2.2 Training/fatigue effects. Each participant was required to complete a randomized order of six decision tasks. The level of alternatives (either three, five or seven) was held constant for each participant. Each subject was then evaluated over two ISS observations on each dimension level (either three, five or seven). Before beginning the six decision task experiment, ISLab took each participant through a set of training exercises (see the discussion in Section 3.4.1). Therefore, some attempt was made to control for training effects. Total time spent at the computer (including the training exercises) ranged from 20 to 60 minutes.

Objective statistical analysis is employed to verify that training or fatigue effects are not confounding the test results. Initially, the order of the six choice tasks was correlated with the ISS variable. A positive or negative correlation between the presentation order of the capital budgeting task and the ISS displayed could indicate shifts in ISS for reasons other than those postulated in this study. The correlation coefficient for the total participant group ($r = -.0256$) was not significant ($p = .56638$). More specifically, the correlation coefficient for the inexperienced participants was not significant ($r = -.0823$; $p = .16363$). The correlation coefficient for the experienced participants was also not significant ($r = .0554$; $p = .41788$). This is evidence that participants are not varying their information search strategy according to the position of a choice task in a stream of capital investment decisions.

A stronger test for training and/or fatigue effects was conducted by examining significant differences in the ISS variable between choice tasks of equal information load for each participant. Significant differences in ISS scores over the same level of information load (alternative and dimension level) would indicate training and/or fatigue effects. ANOVA results show no significant differences between comparable choice tasks for all participants. However, as seen in Table 4.6, there was a small three-way interaction between the levels of both dimension and alternatives and experience distinction within the participant group.

Table 4.6

ANOVA for Training/Fatigue Effects

SOURCE	SS	df	MS	F	Pr > F
Experience	0.11	1	0.11	0.02	0.888
Alternatives	21.04	2	10.52	2.17	0.119
Dimensions	5.50	2	2.75	0.62	0.544
Exper. * Altern.	0.24	2	0.12	0.02	0.968
Exper. * Dimen.	0.89	2	0.45	0.10	0.899
Altern. * Dimen.	25.47	4	6.37	1.44	0.222
Exp. * Alt. * Dim.	44.36	4	11.09	2.51	0.044

$\omega^2 = 3.92\%$

Inspection of the data reveals that at low levels of alternatives, experienced capital budgeters became more compensatory than inexperienced capital budgeters as time progressed. At high levels of alternatives, this trend reversed as experienced capital budgeters became relatively more noncompensatory. However, since only a small proportion of variance in the ISS variable is accounted for by such effects (ω^2 = 3.92%), participants' training or fatigue is not expected to confound results of hypotheses testing.

Since significant differences in the ISS variable between choice tasks of equal information load were generally not observed, further examination of ISS involved averaging the two ISS scores accompanying equal information loads for each participant. Effectively, out of the set of six decision tasks, each participant generated three observations of average ISS for statistical testing purposes.

4.2.3 Gender effects. One final examination for potential confounds, gender effects, was undertaken before hypotheses testing. Of the 36 experienced participants in this study, 2 are female. This unrepresentative gender mix precludes an effective statistical evaluation of gender effects within the group of experienced participants. However, of the 48 inexperience participants (students) in this study, 20 are female. Consequently, ANOVA is used to examine for systematic variance of ISS across gender groups of the student sample. Results for a partial ANOVA table are presented in Table 4.7.

Table 4.7

ANOVA for Gender Effects

SOURCE	SS	df	MS	F	Pr > F
Gender	6.26	1	6.26	0.55	0.462
Gender * Altern.	38.65	2	19.33	1.70	0.195
Gender * Dimen.	4.83	2	2.42	1.58	0.210
Gender * Alt * Dim	7.54	4	1.89	1.23	0.304

$\omega^2 = 2.36\%$

As displayed in Table 4.7, no significant gender effects on the dependent variable, ISS, are observed.

4.3 Hypothesis 1 -- Information Load

4.3.1 Initial ANOVA. Hypothesis 1 ($\mathbf{H}_1$), in null form, states that experienced and inexperienced capital budgeters do not display systematic differences in their information search strategy based on changes in information load attending the contemporary capital investment decision. To examine this hypothesis, the effect on ISS of increasing levels of alternatives and levels of dimensions attending the choice task is evaluated and contrasted across experienced and inexperienced participants in the study. Table 4.8 presents the results of this analysis in ANOVA form.

Table 4.8

ANOVA for Information Load Effects (H_1)

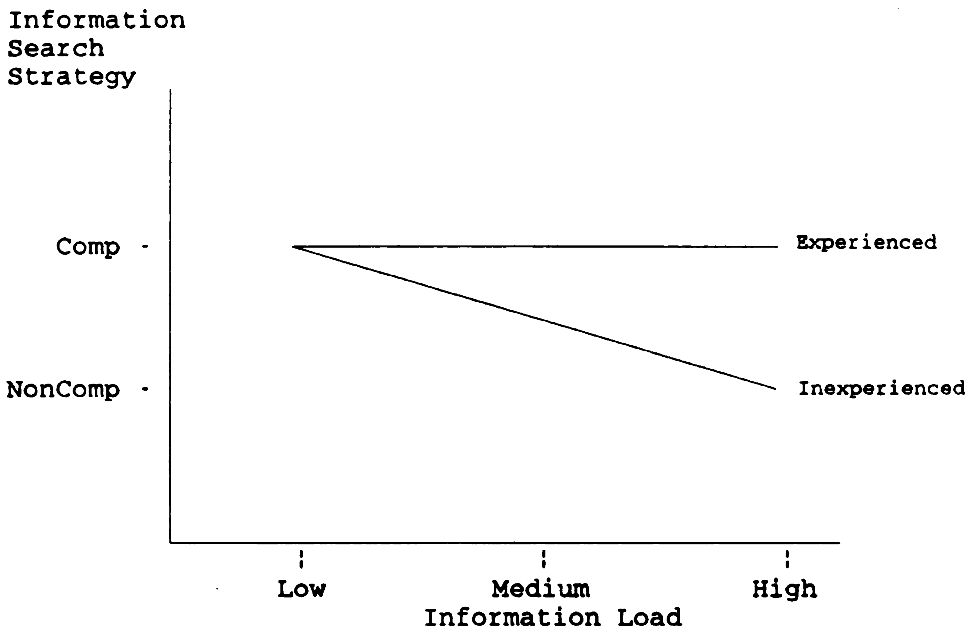
SOURCE	SS	df	MS	F	Pr > F
Experience	5.69	1	5.69	0.53	0.469
Alternatives	100.88	2	50.44	4.68	0.012
Dimensions	124.07	2	62.03	38.77	0.000
Exper. * Altern.	5.60	2	2.80	0.26	0.774
Exper. * Dimen.	1.57	2	0.79	0.49	0.619
Altern. * Dimen.	8.71	4	2.18	1.36	0.246
Exp. * Alt. * Dim.	5.47	4	1.37	0.85	0.498

$\omega^2 = 15.042\%$

As seen in Table 4.8, there are substantial main effects on ISS as a result of changing the levels of both alternatives and dimensions. This supports past research results (Payne, 1976; Biggs et al., 1985; Anderson, 1988). However, experience does not display a main effect or an interaction effect on the decision maker's information search strategy. Yet an inspection of the data indicate a potential trend. Experience seems to result in an ability to operate at more compensatory levels as compared to inexperience in the capital investment decision task. Though the effect is small, this pattern is more pronounced at lower levels of alternatives and dimensions. Such a trend, supported by the previous research of Biggs and Mock (1983) and Krogstad et al. (1984), is depicted in graph form in Figure 4.1. As described in the following section, if this trend truly describes the data, traditional ANOVA inefficiently tests for interactive effects.

Figure 4.1

Experience Remains Relatively Compensatory



4.3.2 <u>Contrast coding</u>. Traditional ANOVA strictly tests for cross-over effects as the only form of interaction among variables (Buckless and Ravenscroft, 1990). Therefore, the interactive effect of such a relationship depicted in Figure 4.1 is spread among the several sources of variance within the ANOVA presented in Table 4.8. To test explicitly the pattern that experienced capital budgeters remain relatively compensatory in their search strategy (as portrayed in Figure 4.1), contrast coding is used. Contrast coding uses the traditional sum of squares formula to weight each cell mean in a manner appropriate to the *a priori* relationship (Buckless and Ravenscroft, 1990):

$$\text{SSmodel} = \frac{s_h[\Sigma(c_i)(\text{EAD}_i)]^2}{\Sigma(c_i)^2}$$

where:

SS = sum of squares
s_h = harmonic mean number of subjects per cell
c = weights assigned to the cell means
i = cell identifier, and
EAD = cell means.

Given the presence of unequal sample sizes within this experiment (see Table 3.2), Keppel (1982) suggests use of an average group size. The average group size (the harmonic mean) is found by dividing the total number of treatment means by the sum of the reciprocals of the various sample sizes. The harmonic mean is consistently applied throughout this study's analysis.

To ensure estimation of population parameters, ANOVA requires that the weights for each contrast sum to zero. This requirement is satisfied by the set of coefficients in Table 4.9 used to capture the *a priori* relationship. As the information load increases, the coefficients portray the experienced capital budgeter generating a consistently high ISS score (indicative of a compensatory strategy) while the inexperienced capital budgeter progressively moves toward a noncompensatory information search strategy (as seen in Figure 4.1). Beneath each coefficient, in parentheses, is the observed cell mean. The harmonic cell size for this data run is 13.67.

Table 4.9

Contrast Coding for H_1

(Cell means are in parentheses)

	3 Dimensions	**5 Dimensions**	**7 Dimensions**
3 Alternatives Inexperience	1 (1.38)	0 (0.56)	-1 (0.20)
Experience	1 (1.30)	1 (1.02)	1 (0.50)
5 Alternatives Inexperience	0 (0.37)	-1 (-0.77)	-2 (-1.30)
Experience	1 (1.67)	1 (-0.14)	1 (-1.32)
7 Alternatives Inexperience	-1 (0.46)	-2 (-0.67)	-3 (-1.65)
Experience	1 (0.43)	1 (-0.96)	1 (-1.16)

The result of this contrast coding amends the original ANOVA. A partial ANOVA, presented in Table 4.10, displays a significant F value for this particular relationship. This amended ANOVA does not explain additional variance among the data. Rather, as stated above, use of contrast coding accurately unites variance appertaining to the hypothesized relationship that traditional ANOVA spreads among other main and interactive effects. Hence, the ω^2 for the entire ANOVA presented in Table 4.8 also relates to the partial ANOVA in Table 4.10. Therefore, tests for specific relationships between experience and information load results in a rejection of the null hypothesis.

Table 4.10

Partial ANOVA for H_1 Contrast Coding

SOURCE	SS	df	MS	F	Pr > F
H_1 Model	5.34	1	5.34	3.34	0.086

Compared to inexperienced decision makers, experienced decision makers are consistently more systematic and thorough in their information search across various levels and types of information attending the capital investment choice task.

4.4 Hypothesis 3 -- Data Fixation

4.4.1 Initial ANOVA. Hypothesis 3 (H_3), the data fixation hypothesis, examines the effect of information attending past decisions on experienced and inexperienced capital budgeters. The effect on ISS of increasing levels of alternatives and dimensions attending *past* choice tasks is evaluated and contrasted across experienced and inexperienced participants in the study. Table 4.11 presents the results of this analysis in ANOVA form.

Table 4.11

ANOVA for Data Fixation Effects (H_3)

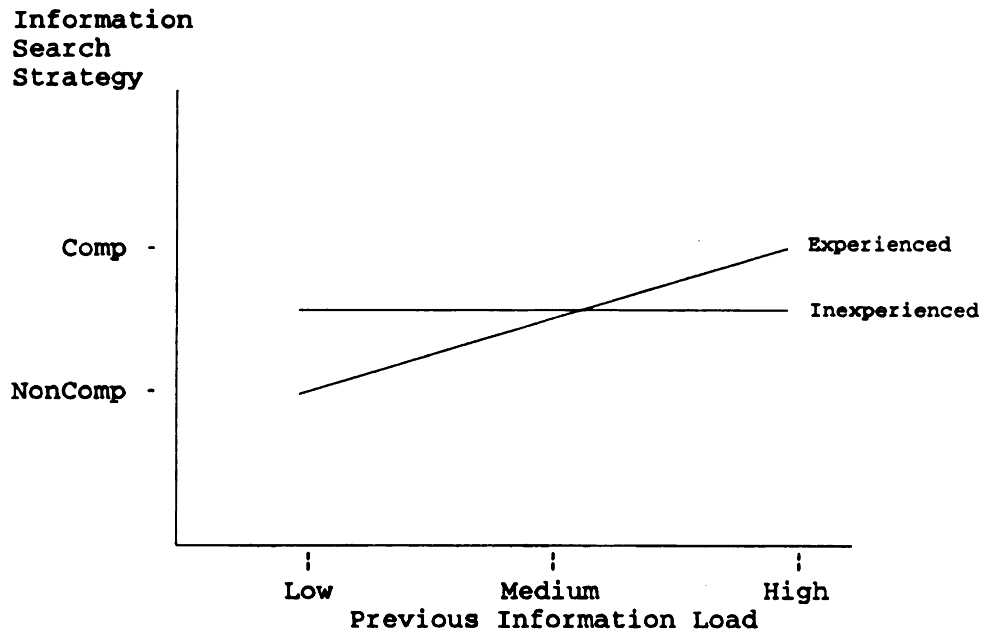
SOURCE	SS	df	MS	F	Pr > F
Experience	13.55	1	13.55	1.27	0.263
Alternatives	110.00	2	55.00	5.15	0.000
Dimensions	21.59	2	10.80	5.05	0.008
Exper. * Altern.	8.45	2	4.22	0.40	0.677
Exper. * Dimen.	0.09	2	0.05	0.02	0.968
Altern. * Dimen.	4.76	4	1.19	0.56	0.695
Exp. * Alt. * Dim.	15.77	4	3.94	1.84	0.123

$\omega^2 = 8.60\%$

As seen in Table 4.11, there are substantial main effects on ISS as a result of changing the level of dimensions attending past, unrelated choice tasks. Since this experimental design is nested on the level of alternatives (independent groups) and crossed on the level of dimensions (repeated groups), effectively participants can only respond to number of dimensions attending previous decisions. The main effect seen for level of alternatives is actually the same information load response previously presented in Section 4.3. It is important to note this strong fixation on data of previous decisions. This result is useful for understanding past research that does not clearly distinguish data and functional fixation, e.g., Bloom et al. (1984) versus Moon (1990).

4.4.2 Contrast coding. The insignificant interaction between experience and past information loads in Table 4.11 does not justify rejection of the null. Yet further inspection of the data indicates a potential trend. Large levels of information load for previous decisions result in a proclivity for more compensatory search strategies for experienced participants. Inexperienced participants are not systematically affected by past levels of information. This trend is depicted in graph form in Figure 4.2. This trend, like Figure 4.1, is not the true cross-over interaction tested by traditional ANOVA. Therefore, contrast codes specific to this *a priori* relationship is employed to strengthen the ANOVA.

Figure 4.2
Experience Reacts to Previous Information Loads



This trend may be the result of a repercussion effect. For example, consider a decision maker struggling to utilize a large set of information. When subsequently presented with a smaller information set attending a new decision, the decision maker feels the new decision set is easier to use as compared to the same decision set following an alternative information set equal or smaller in size. The capital budgeter is more systematic and exhaustive in the search strategy than would otherwise by displayed. This would be one type of a data fixation response, resulting in a rejection of the null hypothesis.

The *a priori* relationship is captured in the set of proposed contrast coefficients presented in Table 4.12. Experienced participants are assumed to move in a compensatory direction as the level of dimensions attending prior decision tasks increase. Inexperienced participants are not expected to shift their search strategy as a result of prior decision tasks. Although higher levels of alternatives cause experienced participants to operate at more noncompensatory levels, the same pattern of movement towards compensatory search strategies emerges as prior decision tasks increase in number of dimensions.

Table 4.12

Contrast Coding for H_3

(Cell means are in parentheses)

	3 Dimensions	**5 Dimensions**	**7 Dimensions**
3 Alternatives Inexperience	0 (0.50)	0 (0.66)	0 (1.12)
Experience	0 (0.84)	1 (1.21)	2 (1.01)
5 Alternatives Inexperience	0 (-0.99)	0 (-0.44)	0 (-0.41)
Experience	-1 (-0.08)	0 (-0.67)	1 (1.56)
7 Alternatives Inexperience	0 (-0.95)	0 (-0.93)	0 (-0.38)
Experience	-2 (-1.02)	-1 (-0.08)	0 (-0.19)

The amended ANOVA, as a result of the contrast coding, appears in Table 4.13. The proposed relationship is significant with a P value equal to 0.0556. Similar to the evaluation of H_1, the ω^2 value for the full ANOVA in Table 4.11 is also associated with the partial ANOVA in Table 4.13. Compared to inexperienced decision makers, experienced decision makers are consistently more systematic and thorough in their information search across various levels and types of information attending the capital investment choice task.

Table 4.13

Partial ANOVA for H_3 Contrast Coding

SOURCE	SS	df	MS	F	Pr > F
H_3 Model	7.96	1	7.96	3.72	0.056

The testing for specific relationships between experience and information loads attending prior decisions results in evidence to reject the null hypothesis. Experienced capital budgeters exhibit a type of data fixation on past information loads. In response to large amounts of information, experienced capital budgets apparently utilized relatively more compensatory information search strategies when analyzing subsequent, unrelated capital investment decisions. This tendency is not evident to the same degree in inexperienced capital investment decision makers.

4.5 Hypothesis 2 -- Functional Fixation

4.5.1 Simple causal chain model. Hypothesis 2 (H_2), in null form, states that experienced and inexperienced capital budgeters are not differently affected in their current information search strategy by information search strategies utilized in past, unrelated capital investment decisions. This hypothesis questions the effect of functional fixation, as opposed to data fixation, on experienced and inexperienced capital budgeters. To examine this hypothesis, the effect of past ISS on the current ISS is analyzed and contrasted across experienced and inexperienced participants in the study. Table 4.14 presents the correlation matrix for the sequential set of ISS observed for both the experienced and inexperienced groups of participants.

Table 4.14

Correlations Among Sequential ISS for the Participants

Panel A: Experienced Capital Budgeters

n = 36

Observed Correlation Matrix

	ISS_1	ISS_2	ISS_3	ISS_4	ISS_5	ISS_6
ISS_1	1.00					
ISS_2	0.78	1.00				
ISS_3	0.54	0.53	1.00			
ISS_4	0.57	0.44	0.44	1.00		
ISS_5	0.45	0.41	0.40	0.43	1.00	
ISS_6	0.52	0.36	0.57	0.55	0.33	1.00

Panel B: Inexperienced Capital Budgeters

n = 48

Observed Correlation Matrix

	ISS_1	ISS_2	ISS_3	ISS_4	ISS_5	ISS_6
ISS_1	1.00					
ISS_2	0.48	1.00				
ISS_3	0.50	0.34	1.00			
ISS_4	0.36	0.56	0.65	1.00		
ISS_5	0.49	0.49	0.56	0.59	1.00	
ISS_6	0.39	0.44	0.51	0.61	0.65	1.00

Path coefficients are generated from the correlation matrices above to test the presence of a simple causal chain model (see Figure 3.9). Evidence of such a chain would support the rejection of the null hypothesis, indicating the presence of functional fixation. Figure 4.3 presents the path coefficients (equivalent to correlation coefficients) generated for both groups of participants based on a simple causal chain. Since each ISS observation is posited in Figure 4.3 to be impacted by a single antecedent ISS observation, the corresponding path coefficient is estimated to be the simple correlation between the two ISS observations seen in Table 4.14. Therefore, for the experienced participants,

$$p_{ISS2,ISS1} = r_{ISS2,ISS1} = 0.78$$

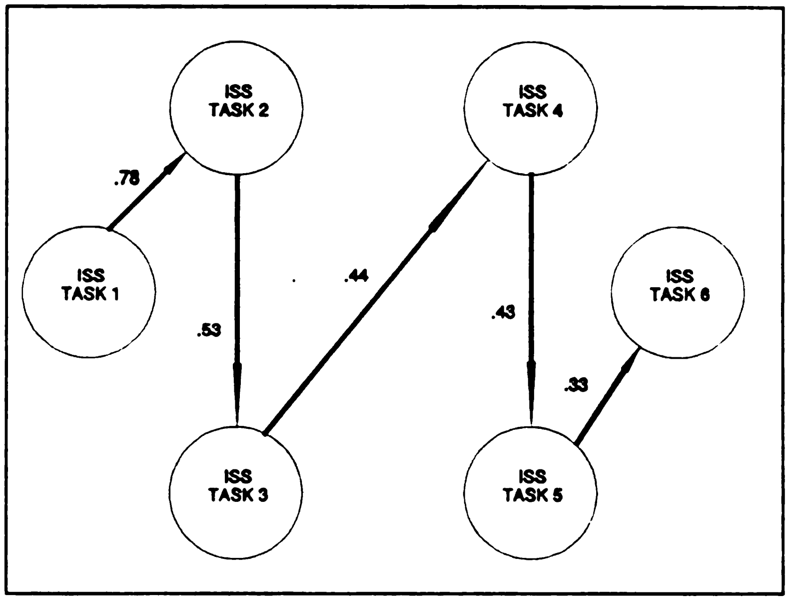
where:

ISSn = the information search strategy observed in choice task n,
p = the corresponding path coefficient between two tasks, and
$r_{ISS2,ISS1}$ = the correlation obtained from Table 4.14, Panel A.

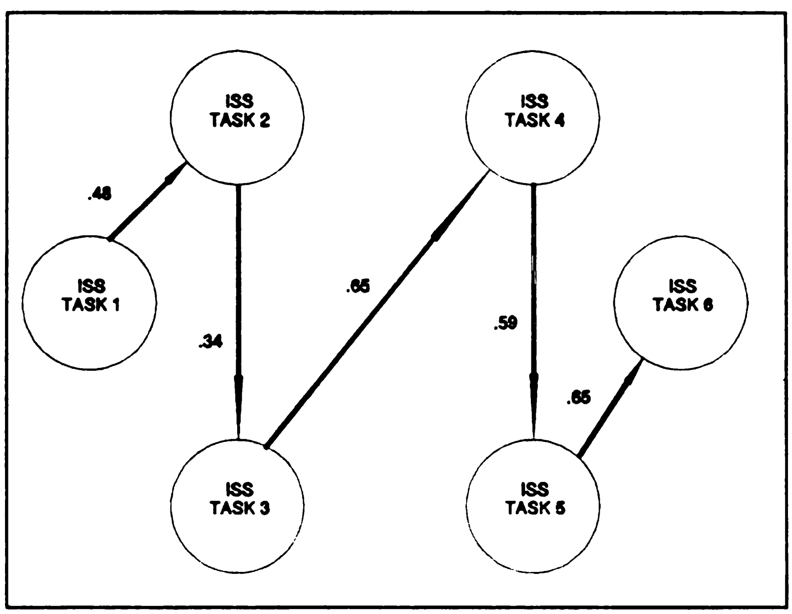
Figure 4.3

Path Model for 1 Antecedent

Panel A: Experienced Participants



Panel B: Inexperienced Participants



Of the fifteen correlations presented for each participant group in Table 4.14, five of those correlations are defined (i.e., constrained) as equal to the proposed path coefficients (i.e., the model is over-identified). Therefore, ten of the correlations are testable using a product rule. The path coefficients, *p*, are used to predict the ten test correlations, **r′**. For example, for the experienced participants,

$$\mathbf{r}'_{ISS3,ISS1} = 0.41 =$$

$$(p_{ISS2,ISS1})(p_{ISS3,ISS2}) = (0.78)(0.53)$$

where:

ISSn = the information search strategy observed in choice task n and
p = the corresponding path coefficient between two tasks as seen in Figure 4.3.

The test correlations, as predicted by the product rule above, are compared to the observed correlations in Table 4.14 to obtain an error (residual) matrix. Residuals of significant size result in rejection of the validity of the simple causal chain model.

The ten test correlations, as predicted by the product rule above, are displayed in the predicted matrices in Tables 4.15 and 4.16 for the experienced and inexperienced participants, respectively. The error matrices, also presented in Tables 4.15 and 4.16, contain the difference between the predicted and actual test correlations.

Table 4.15
Test of Path Model for 1 Antecedent
(Experienced Participants)

Predicted Correlation Matrix

	ISS_1	ISS_2	ISS_3	ISS_4	ISS_5	ISS_6
ISS_1						
ISS_2						
ISS_3	0.41					
ISS_4	0.18	0.23				
ISS_5	0.08	0.10	0.19			
ISS_6	0.03	0.03	0.06	0.14		

Error Matrix (Observed - Predicted)

	ISS_1	ISS_2	ISS_3	ISS_4	ISS_5	ISS_6
ISS_1						
ISS_2						
ISS_3	0.13					
ISS_4	0.39^{***}	0.21^{*}				
ISS_5	0.37^{***}	0.31^{**}	0.21^{*}			
ISS_6	0.49^{***}	0.33^{**}	0.51^{***}	0.41^{***}		

* $p < .10$
** $p < .05$
*** $p < .01$

Table 4.16
Test of Path Model for 1 Antecedent
(Inexperienced Participants)

Predicted Correlation Matrix

	ISS_1	ISS_2	ISS_3	ISS_4	ISS_5	ISS_6
ISS_1						
ISS_2						
ISS_3	0.16					
ISS_4	0.11	0.22				
ISS_5	0.06	0.13	0.38			
ISS_6	0.04	0.08	0.25	0.38		

Error Matrix (Observed - Predicted)

	ISS_1	ISS_2	ISS_3	ISS_4	ISS_5	ISS_6
ISS_1						
ISS_2						
ISS_3	0.34***					
ISS_4	0.25*	0.34***				
ISS_5	0.43***	0.36***	0.21*			
ISS_6	0.35***	0.36***	0.26**	0.23**		

* $p < .10$
** $p < .05$
*** $p < .01$

The residuals in the error matrices are evaluated for size significance using a two-tailed t-test based on n = 36 for the experienced participants and n = 48 for the inexperienced participants. As can be seen in the Error Matrix of Table 4.15, most of the residuals are significant, indicating the failure of the simple casual chain model of ISS for the experienced participants. In the Error Matrix of Table 4.16, again the majority of the ten residuals are significant, indicating similar failure of the simple casual chain model for the inexperienced participants.

Initially, the above results indicate failure to reject the null Hypothesis 2. However, further inspection of the simple correlation matrices indicates the presence of systematic movement, possibly indicative of a more complex casual relationship among the ISS factors attending sequential capital budgeting choice tasks. Specifically, there may be a carry-over effect on the information search strategy resulting from the search strategies utilized in the past *two* choice tasks.

4.5.2 Complex causal path model. By positing that the ISS at time n (ISSn) has multiple causal antecedents (ISSn-1 and ISSn-2), then the path coefficients for ISSn-1 and ISSn-2 are standardized beta weights in the multiple regression of ISSn onto ISSn-1 and ISSn-2 (Hunter and Gerbing, 1982). Therefore,

$$ISSn = a_1 ISSn\text{-}1 + a_1 ISSn\text{-}1$$

where:

$$p_{ISSn-1,ISSn} = a_1 \text{ and}$$
$$p_{ISSn-2,ISSn} = a_2.$$

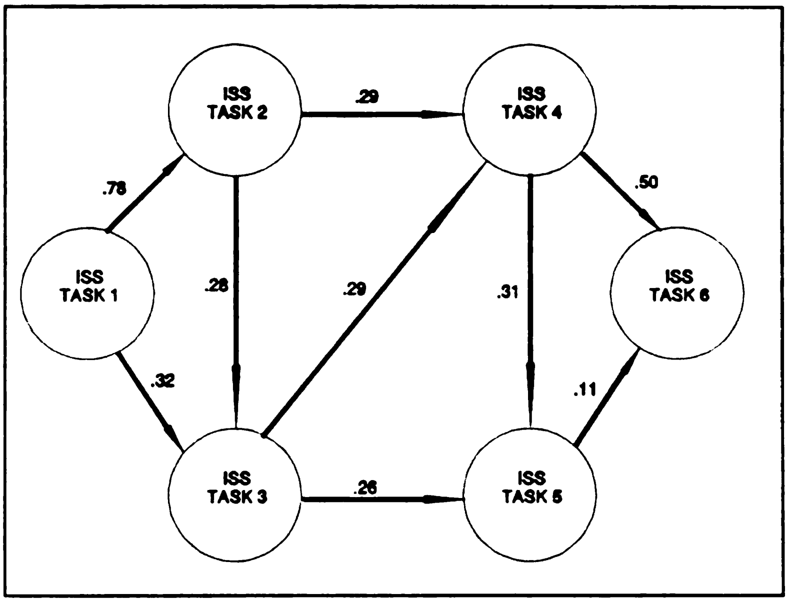
Path coefficients are generated from the correlation matrices in Table 4.14 to test the validity of this more complex path model involving multiple antecedents. Figure 4.4 presents the path coefficients generated for both groups of participants based on multiple antecedents.

In Figure 4.4, each ISS observation is posited to be impacted by the two previous antecedent observations. Therefore, the corresponding path coefficient is estimated to be the multiple regression coefficient. Of the fifteen correlations presented for each participant group in Table 4.14, nine are constrained by the path model as equal to the sum of the direct, indirect and spurious effects (i.e., paths) of the antecedent variable on the dependent variable (Lewis-Beck, 1974; Hunter and Gerbing, 1982). Therefore, the remaining six correlations are testable using a product rule.

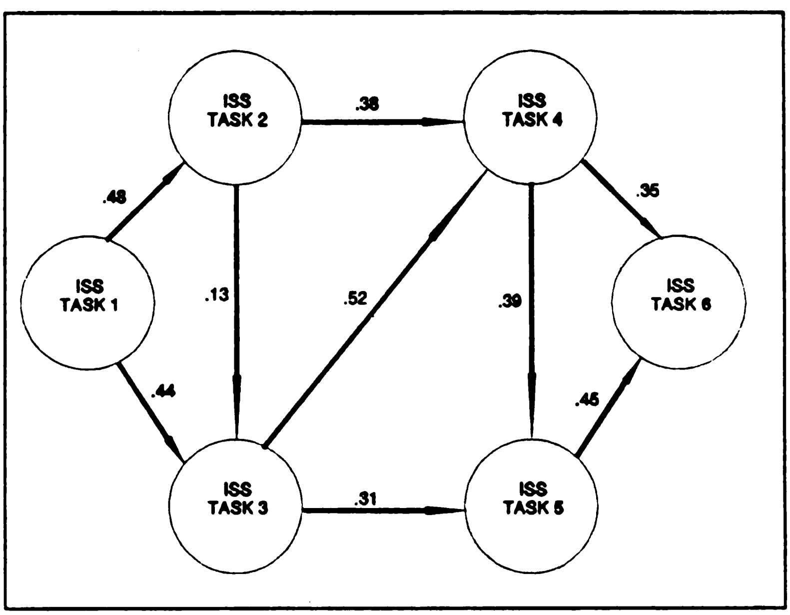
Figure 4.4

Path Model for 2 Antecedents

Panel A: Experienced Participants



Panel B: Inexperienced Participants



Each of the six test correlations are predicted to be the result of indirect and spurious effects of one variable on another variable. For example, according to the path model depicted in Figure 4.4, ISS_2 is posited to have indirect effects on ISS_5 through two intermediate variables, ISS_3 and ISS_4. The indirect effect of ISS_2 on ISS_5 is the sum of the indirect impact determined for each path from ISS_2 to ISS_5. The impact of a path from ISS_2 to ISS_5 is the product of the path coefficients along that path. For example, for the experienced participants, the total indirect effect of ISS_2 on ISS_5 is

$$(p_{ISS4,ISS2})\cdot(p_{ISS5,ISS4}) + (p_{ISS3,ISS2})\cdot(p_{ISS4,ISS3})\cdot(p_{ISS5,ISS4}) + (p_{ISS3,ISS2})\cdot(p_{ISS5,ISS3})$$
$$= (.29)(.31) + (.28)(.29)(.31) + (.28)(.26) = .19$$

where $p_{x,y}$ = the corresponding path coefficient taken from Figure 4.4, Panel A.

ISS_2 and ISS_5 have one common antecedent variable, ISS_1. Each combination of paths from ISS_1 to ISS_2 and ISS_5 generates a contribution to the spurious effect, the product of the path coefficients on *both* paths. The net effect for the common antecedent, ISS_1, is the sum of the products across all combinations of paths to ISS_1 to ISS_2 and ISS_5. Therefore, the total spurious effect for ISS_2 and ISS_5 is

$$(p_{ISS2,ISS1}),(p_{ISS3,ISS1}),(p_{ISS4,ISS3}),(p_{ISS5,ISS4})$$
$$+ (p_{ISS2,ISS1}),(p_{ISS3,ISS1}),(p_{ISS5,ISS3})$$
$$= (.78)(.32)(.29)(.31) + (.78)(.32)(.26) = .09$$

where $p_{x,y}$ = the corresponding path coefficient taken from Figure 4.4, Panel A.

The predicted correlation between ISS_2 and ISS_5 for the experienced participants is the sum of the indirect and spurious effects determined by the path model as follows,

$$r'_{ISS2,ISS5} = \text{the Indirect Effect} + \text{the Spurious Effect}$$
$$= .19 + .09 = .28.$$

The test correlations, as predicted by the product rule demonstrated above, are displayed in the predicted matrices in Table 4.17 and 4.18 for experienced and inexperienced participants, respectively. These test correlations are compared to the observed correlations in Table 4.14 to obtain the error matrices (also displayed in Tables 4.17 and

4.18). Residuals of significant size result in rejection of the path model depicted in Figure 4.4.

Table 4.17
Test of Path Model for 2 Antecedents
(Experienced Participants)

Predicted Correlation Matrix

	ISS_1	ISS_2	ISS_3	ISS_4	ISS_5	ISS_6
ISS_1						
ISS_2						
ISS_3						
ISS_4	0.38					
ISS_5	0.26	0.28				
ISS_6	0.22	0.25	0.27			

Error Matrix (Observed - Predicted)

	ISS_1	ISS_2	ISS_3	ISS_4	ISS_5	ISS_6
ISS_1						
ISS_2						
ISS_3						
ISS_4	0.19*					
ISS_5	0.19	0.13				
ISS_6	0.30***	0.11	0.30***			

* $p < .10$
** $p < .05$
*** $p < .01$

Table 4.18

Test of Path Model for 2 Antecedents (Inexperienced Participants)

Predicted Correlation Matrix

	ISS_1	ISS_2	ISS_3	ISS_4	ISS_5	ISS_6
ISS_1						
ISS_2						
ISS_3						
ISS_4	0.44					
ISS_5	0.33	0.32				
ISS_6	0.30	0.34	0.48			

Error Matrix (Observed - Predicted)

	ISS_1	ISS_2	ISS_3	ISS_4	ISS_5	ISS_6
ISS_1						
ISS_2						
ISS_3						
ISS_4	-0.08					
ISS_5	0.16	0.17				
ISS_6	0.09	0.10	0.03			

* $p < .10$
** $p < .05$
*** $p < .01$

As seen in the Error Matrix of Table 4.17, two of the six residuals for the experienced participants are significant in size and one residual is potentially significant. Therefore, the divergence of observed correlations from those predicted by the proposed path model displayed in Figure 4.4 indicates failure of that model for the experienced participants. However, in Table 4.18, the size of each of the six residuals for the inexperienced participants are all insignificant. Hence, the proposed path model obtains for the inexperienced participants. This group displays carry-over effects on their information search strategy from unrelated search strategies attending the preceding two capital investment choice tasks. This finding results in a rejection of the null Hypothesis 2.

Based on the path analysis above, the contemporary information search strategies of experienced and inexperienced capital budgeters are affected differently by past capital investment information search strategies. The correlation matrices in Table 4.14 were further inspected and similarly tested to determine the validity of an alternative path model other than the models examined above for the experienced participants. No such model was determinable. In performing the six capital budgeting choice tasks, the experienced participants did not display any systematic reliance on previous, unrelated information search strategies. Therefore, only the inexperienced participants displayed any tendency of functional fixation.

4.6 Summary

The experimental results and data analysis were presented in this chapter. The first section presented the development of a unidimensional measurement model of information search strategy (ISS). Confirmatory factor analysis revealed that the initial model based on the indicators Proportion Searched (PS), Variability in Proportion Searched across Alternatives (VA), Variability in Proportion Searched across Dimensions (VD), and Search Direction (SD) is inappropriate. Subsequent analysis determined that PS, VA and VD satisfactorily combine to form a unidimensional model of ISS. This model was then used for hypothesis testing. Based on both theoretical and analytical problems, the SD indicator was not used in hypotheses testing involving shifts between compensatory and noncompensatory information search strategies.

Before testing the hypothesis, manipulation checks were presented in the second section of this chapter. Analysis for potential training, fatigue and gender effects was also presented. Manipulation of information load for each capital investment choice task was satisfactory. No confounding effects of training, fatigue or gender were noted.

Section 3 reported the results on Hypothesis 1 testing. Using contrast coding, it was revealed that experienced capital budgeters remain relatively compensatory in their ISS compared to inexperienced capital budgeters. The inexperienced group displayed effects of information load as demonstrated by their movement towards noncompensatory ISS as the information load of capital investment choice tasks was increased. This evidence resulted in a rejection of the null Hypothesis 1.

Section 4 reported the results on Hypothesis 3 testing. Using contrast coding, it was revealed that experienced capital budgeters react to high levels of information load accompanying *past* capital investment choice tasks. This reaction, a type of data fixation, is displayed as a movement towards more compensatory ISS in the *current* capital investment choice task. Inexperienced capital budgeters did not display any form of systematic data fixation, resulting in a rejection of null Hypothesis 3.

Section 5 reported the results on Hypothesis 2 testing. Using path analysis, neither the experienced nor the inexperienced group of capital budgeters emulated a functional fixation on the ISS utilized in the most recent choice task. However, further investigation disclosed that inexperienced capital budgeters do display carry-over effects from the *two* most recent choice tasks -- a more complex version of functional fixation. Experienced capital budgeters display no systematic pattern of fixation on past ISS, resulting in a rejection of null Hypothesis 2. A discussion of these findings follows in the next chapter.

CHAPTER V

CONCLUSION

5.0 Overview

In this chapter, a summary of the research results is presented, including a discussion of the implications, contributions and limitations of the current study. Also included are suggestions for future research. A summary of the research results is presented in the first section. In Section 2, implications and contributions based on the results of this study are offered. The third section describes limitations of this study. Suggestions for future research are contained in Section 4.

5.1 Summary of Results

5.1.1 Information load research question (H_1). The initial research question of this study asks what effect increasing amounts of information has on the decision processes of inexperienced and experienced capital budgeters. A review of research literature to date does not allow the reader an unequivocal position on the interaction of the capital budgeter's experience and his or her use of information in decision making.

For example, research such as Biggs and Mock (1983), Krogstad et al. (1984) and Johnson (1985) suggests that as the level of information attending the capital investment task increases, inexperienced capital budgeters are more systematic and thorough (i.e. compensatory) in their information search compared to experienced capital budgeters. However, research such as DeGroot (1965), Schroder et al. (1967), Newell and Simon (1972) and Hershey et al. (1990) would indicate otherwise. The apparent conflict in the literature suggests the need to further examine effects of information load prior to designing decision support systems (DSS) for decision makers who differ in their capital budgeting experience. Therefore, in this study, the amount of information attending a series of capital budgeting tasks was manipulated for two groups of participants differentiated by their level of experience.

In the current study, varying the level of alternatives or the level of dimensions creates a main effect on the capital budgeter's information search strategy. Specifically, increasing levels of alternatives or dimensions results in a shift to more noncompensatory search strategies. This outcome supports past research, such as Biggs et al. (1985), relative to information load effects. More specific analysis using contrast coding suggests that experienced capital budgeters are not as susceptible to this information load effect. Experienced capital budgeters utilize more compensatory levels of information search. Thus, as information load increases, experience results in an ability to be more systematic and more exhaustive in the search through capital investment data. These results support the rejection of H_1.

5.1.2 Fixation research question (H_2 and H_3). The second research question explored by this study asks what effect capital budgeting experience has on the tendency for individuals to be fixated on factors attending previous capital budgeting tasks. Accounting research has not clearly resolved the issue of whether experience diminishes symptoms of decision making fixation (e.g. Barnes and Webb, 1986; and Paquette and Kida, 1988) or, in fact, engenders fixation (Haka et al., 1986; Davis and Solomon, 1989; and Frensch and Sternberg, 1989).

Initially, this research question also must resolve apparent uncertainty in accounting literature on the very definition of fixation. Fixation has often been addressed in accounting literature without explicitly differentiating between fixation on accounting information (e.g. data fixation as seen in Ashton, 1976; Chang and Birnberg, 1977; Bloom et al., 1984; and Barnes and Webb, 1986) from fixation on how to *use* accounting information (e.g. functional fixation as seen in Wilner and Birnberg, 1986; and Moon, 1990). Similar to previous work, this study investigates the presence of fixation among decision makers in the capital budgeting arena. However, two important enhancements of past research are made. First, functional fixation and data fixation are clearly distinguished and individually tested. Second, effects of these two types of fixation are examined across capital budgeters with different levels of experience. H_2 tested for functional fixation effects among experienced and inexperienced capital budgeters. H_3 tested for data fixation effects among experienced and inexperienced capital budgeters.

Initially, functional fixation was tested by examining for presence of some type of causal model that describes a dependency on search strategies used in prior capital budgeting tasks. Path analysis uncovered inexperienced capital budgeters' dependence on the previous two information search strategies, describable as a second-order autoregressive dependency. On the other hand, experienced capital budgeters did not display evidence of any carry-over effects from particular information search strategies used in previous decision tasks. Therefore, H_2 is rejected.

The results of this study also indicate carry-over effects of *information* attending previous, unrelated capital budgeting decisions. Overall, capital budgeters' information search strategies display a data fixation effect. The use of contrast coding reveals that the trend relates to the level of experience attained by the capital budgeter. Essentially, experienced capital budgeters's, though not affected by past use of a particular decision strategy, were affected by exposure to information attending past decisions. This propensity is described earlier

(Section 4.2.2) as a repercussion effect. In other words, large amounts of information attending previous capital investment choice tasks result in an increased use of compensatory strategies in the current capital budgeting task. An information search strategy preceded by an unrelated choice task with relatively lower levels of attending information is characteristically less systematic and exhaustive. Therefore, H_3 is rejected.

To summarize the fixation question addressed in this study, it is seen that both inexperienced and experienced capital budgeters display fixation tendencies. However, the nature of this fixation phenomenon differs among the two types of capital budgeters. The inexperienced participants are functionally fixated on previous information search strategies. Conversely, experienced participants are fixated on previous, unrelated data. These results, compared to previous studies, provide more comprehensive insight into the fixation issue as it relates to capital budgeting. This new insight specifically pertains to the data fixation versus functional fixation of experienced and inexperienced capital budgeters.

5.2 Implications and Contributions

"The scarce resource today is not information, but the ability to process it" (Simon, 1977, p. 108). The results of the current study supports Simon's position. Most discussions of capital budgeting do not emphasize important relationships between the firm's information system and the way capital budgeting decisions are made (Gordon and Pinches, 1984). The results of this study relative to information load suggests that capital budgeters are systematically affected in their decision process by information presented in the task. These results indicate that the capital budgeting DSS should be an information compressor -- designed to receive more information than it transmits. This bounded rationality mode of capital budgeting suggests that the DSS designer should consider the effect of increasing numbers of capital investment alternatives or information dimensions related to each alternative on the system user -- especially the inexperienced user.

Two design approaches are suggested here. (1) The designer may develop a DSS to better filter, rather than proliferate, capital budgeting information (Simon, 1977). (2) The DSS can be designed to structure the capital budgeting task in order to promote the decision process desired by the organization. For example, Stout, Liberatore and Monahan (1991) describe a capital budgeting DSS that promotes a compensatory information search strategy by automatically performing many of the compensatory functions for the decision maker. These support functions include using pairwise questions to derive the capital budgeter's inherent dimension weights, helping the individual derive dimension scores across investment alternatives, then combining weights and scores to determine a ranking of alternatives. One benefit of such a DSS design strategy is the flexibility to assign more administrative and strategic capital investment decisions to less-experienced individuals within the organization.

Fixation research in the decision task is not as well-developed as information load research. This study increases understanding of the fixation phenomenon in the capital budgeting task. Fixation results are still exploratory and needs to be extended. However, the evidence that capital budgeters display fixation effects indicates that the DSS needs to be more than just an information compressor. In addition to information load effects, capital budgeting effectiveness may be impaired by factors not directly connected with the decision task at hand, as described below.

For experienced capital budgeters, the DSS should monitor the amount of information received in previous decision tasks. A capital investment decision task preceded by other decision tasks containing undemanding information loads is not as exhaustively evaluated by experienced capital budgeters as the same decision preceded by decision tasks containing large information loads. By tracking the history of capital budgeting within organization, the DSS can be designed to appropriately promote use of more compensatory or more noncompensatory search strategies by the system user. Procedures used to promote compensatory strategies are similar to those described above in the work of Stout et al. (1991). On the other hand, DSS protocol promoting noncompensatory search strategies could, for example, include use of a heuristic such as a cut-off criteria to initially pare down a large set of capital investment alternatives before allowing more systematic and exhaustive methods of information search.

Based on the data analyzed in this study, the organization must also be cognizant of the performance of the inexperienced capital budgeters who are functionally fixated on strategies utilized in past decisions. Inadequate decision performance in one task, characterized by adherence to a undesirable information search strategy, is carried forward to affect at least two more capital investment decisions. Designers of capital budgeting DSS, who are aware of this fixation effect, can develop systems that track and evaluate the inexperienced decision maker's past search strategies. Then, using similar techniques suggested above, inadequate decision performance is rectified through design of a capital budgeting DSS that promotes more desirable decision strategies.

Haynes and Solomon (1962) argue that phases in the capital budgeting decision other than the actual selection phase must be emphasized in research. Specifically, they note:

> Our case studies suggest that the highest priorities should be assigned to the search for alternatives, the search for information, and the correct processing of the available data *before* ranking formulas are applied (p. 46).

Understanding potentials for bias in the pre-selection phases of the capital budgeting decision should provide the DSS designer with requisite insight and motivation to work for supervision of these potential biases. Design approaches similar to those suggested above for controlling information load effects may provide desired results.

5.3 Limitations

Considerable research exists regarding effects of information load and decision maker fixation. However, little research exists describing implications of experience on information load and fixation. Additionally, accounting research has been inadequate in clearly distinguishing functional fixation versus data fixation. This study attempts to bridge gaps specific to capital budgeting in a computerized setting. However, several limitations of this study should be noted.

First, developing an accurate map of the cognitive process is very difficult. There can be no direct observation of the capital budgeting decision process -- or, for that matter, any decision process. ISLab, while providing some advantages over other process-tracing techniques, still yields second-hand knowledge of the capital investment decision process. Therefore, some cognitive aspects of the capital budgeter's information search strategy is not fully captured by ISLab.

Second, participants were required to evaluate a large number of capital budgeting cases in a short time. To eliminate fatigue effects, a mixed research design was used. Manipulating the level of alternatives between, rather than within, subjects likely results in some differences in the analysis of alternatives versus dimensions. It is important to replicate this work, allowing the level of alternatives to be manipulated within subjects. This would provide further insight on the density effect described within this study.

Decision tasks in this study were limited to a maximum of seven capital investment alternatives each defined over seven dimensions (a total of 49 cues). As noted in Section 4.2.1, it is important for later replications of this work to increase the diversity in levels of alternatives and dimensions. Actual capital budgeting involves much higher levels of information load than were presented in this study's experiment. However, it is expected that larger differences in levels of alternatives and dimensions manipulated results in more extreme display of the information load and fixation effects, further supporting the implications of this study.

Similar to other research work, the results of this study cannot be generalized beyond the type of participants employed in this study. Student participants all came from a single midwestern university. Perhaps more importantly, experienced participants in this study tended to center around a particular industry, automotive manufacturing (see Table 4.1). Another group of participants might act differently from those in this study. Replications are needed to assess the pervasiveness and robustness of the findings of the current study.

5.4 Future Research

The empirical findings of this study provide direction for future research endeavors. First, as indicated in Section 2, the nature of this study, especially as it relates to fixation, is somewhat exploratory. The idea that experienced capital budgeters are data fixated and inexperienced capital budgeters are functionally fixated needs to be further pursued. Replicating these results with a different set of participants from a different industry and geographic region would strengthen the validity of the findings. Additionally, researchers should search for similar effects in decision environments other than capital budgeting.

The computerized process-tracing technology does not fully capture all aspects of the capital budgeter's cognitive process. It is argued in this study that the process-tracing technology used provides significant advantages over other alternatives. However, it would be a useful extension of this work if the experiment were replicated using ISLab combined with another process-tracing methodology such as verbal protocol analysis. Consensus on the participant's mental decision process between the two methods would enhanced the legitimacy of these results. Such a triangulation approach to validating the research instrument and better measuring the dependent variable, Information Search Strategy, is supported by other researchers such as Payne, Braunstein and Carroll (1978).

Alternative independent variables affecting the dependent variable, Information Search Strategy, needs to be examined. For instance, this study carefully differentiated the effects of the independent variable information load from the issue of information overload. The information load emphasis contrasts with previous work by examining the ability of experience to diminish the effects of information load on the capital budgeting process. A useful extension of this study is to examine the interaction of experience and information *overload* in the capital budgeting task in a similar fashion. Such an approach would likely require the researcher to establish a measure of capital budgeting quality as it relates to the information search strategy (not done in this study) and correlate this quality measure with increasing levels of information across different levels of capital budgeting experience.

One new contribution to the decision process literature is the focus on the capital budgeters' level of experience as an independent variable affecting information search strategy. Cognitive characteristics of those educated-as-to-capital budgeting is differentiated from those experienced-as-to-capital budgeting (Gibbins, 1988). This study did not attempt to define those experienced-as-to-capital budgeting from those expert-as-to-capital budgeting. Since it is reasonable that experienced capital budgeters will display different levels of expertise, future work should distinguish the effect of experience from the effect of *expertise* on the fixation and information load phenomenon. The work of others such as Bonner and Lewis (1990), which suggests methods for directly establishing the expertise of an experienced decision maker, is useful for such a replication.

Finally, this study documents instances where capital budgeters, differentiated by level of experience, display systematic trends in their information search strategy relative to fixation and information load effects. However, little attempt is made to determine *why* these tendencies exist and *how* they may be influenced by the DSS designer.

Arguments advanced by others such as Wilner and Birnberg (1986) would suggest that these issues must be resolved before insight developed in this study can be incorporated into actual capital investment DSS. Some efforts in this direction have been attempted in a study to determine price setting for contract work (Barnes and Webb, 1986). More empirical effort, specific to the capital budgeting arena, must be invested in delineating the attributes of experience and inexperience that are associated with the information load and fixation effects observed in this study. Researchers and designers must comprehend exactly how the interaction of task, system, and decision-maker characteristics engender information load and fixation effects and how to influence those effects. As this comprehension is developed, large advances in the integration of DSS development with decision maker characteristics will be realized.

5.5 Summary

In summary, this study examines information effects on capital budgeters with differing levels of experience. Section 1 reports the results of this study indicating that increased information causes inexperienced capital budgeters to be less systematic and thorough in their decision process compared to experienced capital budgeters. Additionally, inexperienced capital budgeters display fixation on decision processes used in previous, unrelated capital budgeting tasks. On the other hand, experienced capital budgeters are affected by information attending previous, unrelated capital budgeting tasks. Section 2 describes the possible enhancements of capital budgeting decision support systems engendered by the insight gathered from this study. Cautions to be considered when adopting knowledge obtained from this empirical study are outlined in the third section of this chapter. Finally, in Section 4, suggestions for future research related to information effects on capital budgeters are offered. The most important suggestions include determining similar differences between experienced and expert capital budgeters. Also, future research should concentrate on discovering why these decision process differences occur and how the information system designer might build such knowledge into the decision support system for capital budgeting.

APPENDIX A

NOVICE PARTICIPANTS' INSTRUCTIONS AND QUESTIONNAIRE

ISLab Experiment Package Cover Sheet

Novice Participants

Thank you for your support of research at
The Graduate School of Business Administration,
Michigan State University.

In this packet you should find:
1) ISLab Purpose of Study and Instructions
2) ISLab System Instruction Diagram
3) ISLab Questionnaire
4) ISLab 5 1/4" diskette
5) $1.00 initial payment (More to come!)

Put the ISLab disk in the boot drive and reboot your machine (press [Ctrl]-[Alt]-[Del] simultaneously). Alternatively, you may switch to the appropriate disk drive, then type "GO" and press [Enter].

If requested, please enter Today's Date. The machine will run for a moment before requesting some additional information. After entering the required data, read your ISLab Purpose of Study and Instructions. Proceed through the ISLab session, using the instructions and diagram whenever needed.

Please try to use the computer to do all your decision-making work. If you feel you must make notes or calculations outside of the computer, please include your notes and calculations with the other ISLab materials.

When the final task is completed, the computer will tabulate your final payment which you will receive after completing the questionnaire. If others are waiting to use your machine, have the experiment administrator note the final payment amount <u>before</u> you leave your computer. Please complete the questionnaire. Write your name on the disk, the questionnaire, and all other ISLab materials. Place everything back into the packet, write your name on the outside and give it to the experimenter. Be sure to sign for and receive any final payment.

If you have any questions or problems, contact Monte Swain at MSU's Department of Accounting, (517) 355-7486.

ISLab Pre-Test Instructions

Novice Participants

ISLab

PURPOSE OF THE STUDY

The purpose of this study is to gain systematic knowledge of the capital investment decisions process. While you are performing the task, the computer will record your selections. Analysis of this data will provide a basis for the development of a detailed descriptive model of capital investment decision making. The model in turn will provide a basis for the development of computer-based decision aids to assist company management responsible for similar decisions. This study should take about one hour to complete.

The aggregated information gathered from this study will be available for your inspection and possible use. All individual information gathered will be kept strictly confidential. At the end of the experiment, you indicate your voluntary agreement to participate by completing and returning the questionnaire attached to this instruction sheet.

You will be paid a small monetary reward based your completion of the experiment and the questionnaire and on how closely your answers during the experiment are in agreement with a group of industry experts.

INSTRUCTIONS

I. SITUATIONAL ASSUMPTIONS

Assume you are a manager for a large company in need of modernizing a significant segment of the production process. In each of the following decision situations, there are various numbers of investment alternatives available, each requiring a significant expenditure. All investments have an expected life of 10 years. The cost of each investment is within the company's budget constraints. Your task will be to select <u>one</u> and only one capital investment <u>in each situation</u>.
Your company's current need to update its production process and the significant cost to acquire any of the alternatives considered makes the tasks a rather significant investment decision. You should use as much time and information as you feel is <u>necessary</u> for making your decision. Use the computer for all information needs, i.e., please do not make notes to yourself on a separate piece of paper.

II. DECISION SITUATIONS

There are six independent decision situations. In each decision situation you are to choose one capital investment from a set of possible alternatives. Each investment will be represented by various items of information. Additional explanation of each information item is found at the end of these instructions. The information is both quantitative and qualitative in nature. The quantitative data will be given in its natural numerical form (dollars, percentages, etc.) Qualitative data will be represented on a five-point scale ranging from Very Low to Very High:

(1) Very low (2) Low (3) Average (4) High (5) Very High

Considerable care was taken to make sure that these capital budgeting situations use information typical of similar investment decisions in industry.

III. THE SYSTEM

The system you will interact with to gather information for the task has three parts:

1. An automatic demonstration
2. A hands-on practice decision situation
3. The six actual decision situations

A. The Automatic Demonstration

A series of steps will be displayed that show how the program operates. This is the same sequence of steps you will be using to make your selections. In the demonstration, the task is to choose a potential employee to hire based on information about GPA, experience, desired salary, and self-motivation (referred to as dimensions). Do not make entries. In this demonstration, the computer will make all entries for you.

Use the attached System Instruction Diagram to follow the automatic operations of the computer. Upon completion of the automatic demonstration you will be prompted to either run another demonstration or to start the sample decision. You may repeat the demonstration if desired.

B. The Sample Decision

In the sample decision, the task again is to select an employee to hire. This time _you_ should respond to the prompts on the screen. All of the steps are the same as described above.

Upon completion of a sample decision, you may either repeat the sample or start the actual decisions.

C. THE ACTUAL DECISIONS

There are six independent decision situations. As described earlier, your task will be to select one capital investment alternative in each decision situation. The sequence of entries is the same as in the samples and as described in the System Instruction Diagram. If you make a mistake when selecting an investment, please indicate on the questionnaire.

You will soon see that ISLab does not present the entire set of information for the each decision task all at once. Please try to work with the computerized format given. If possible, please do not make separate notes and calculations as you work.

A group of industry experts have recently completed these same six decision situations. At the end of the experiment, the computer will automatically tabulate additional compensation based on investment selections in agreement with industry experts.

At the conclusion of the experiment, be sure to complete the attached questionnaire.

IV. EXPLANATION OF DIMENSIONS

NPV - Net Present Value. A summation of the investment's discounted cash flows and initial cost using the hurdle rate appropriate for this investment type.

Initial Cost - The total cost of purchase, including transportation and set-up costs.

Risk - A general assessment of the inherent risk of this investment, including potential problems with predicting and controlling its future cash flows. The investment's risk may range from very high to very low.

Payback - The number of years required to recover the initial investment.

Estimation Uncertainty - The level of uncertainty attending the estimation of the investment's future cash flows. Low uncertainty reflects confidence in forecasting the investment's future. High uncertainty indicates that future cash flow are unreliable.

Operating Leverage - The investment's commitment to unavoidable fixed costs. Low leverage reflects an ability to reduce future operating costs in crisis times. High leverage denotes inflexibility.

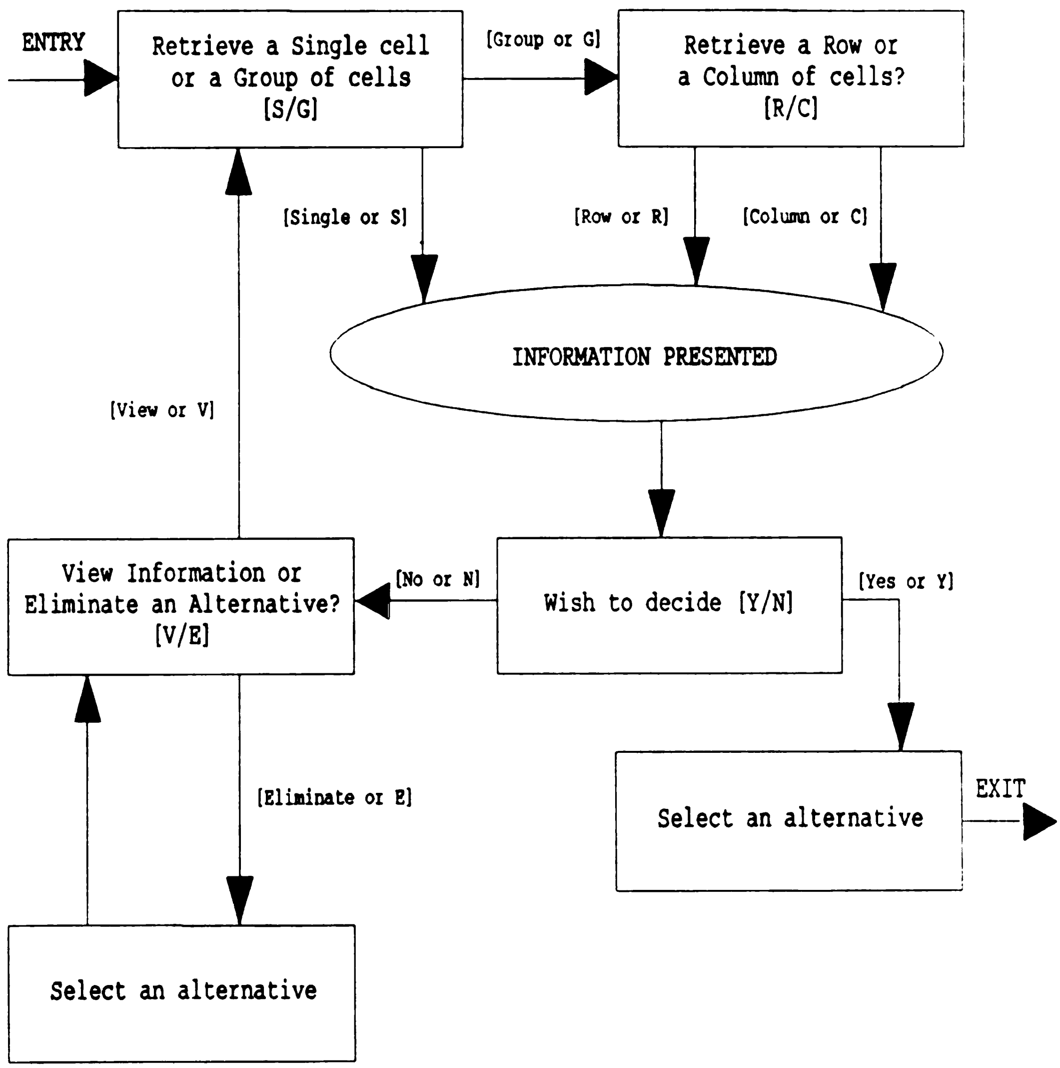
IRR - Internal Rate of Return. The investment's discounted return on its initial cost. At this rate, the NPV = 0.

Annual Net Cash Flow - The investment's annual future incremental cash flow.

Hurdle Rate - The minimal rate of return required by the company for this particular investment's risk. A high hurdle rate indicates a risky investment. This rate is used to generate actual NPV.

ISLab

SYSTEM INSTRUCTION DIAGRAM



ISLab Post-Test Questionnaire

Novice Participants

ISLab

QUESTIONNAIRE

Name ____

Name of School __________________________

Year in School ___________ (Sr, Jr, etc.)

School Major ___________________________

Female ____ Male ____ Age _____

Phone Number ____
(Occasionally, clarification of some responses is required.)

Finance 391 _________________________________
(Completed, Currently Enrolled, or Not Taken)

Grade or Expected Grade in Finance 391 _____________
(voluntary, but appreciated)

* On a scale of 1 to 10, please rate yourself as an experienced user of microcomputers. Assume 10 represents an individual with significant daily experience using a computer as a programming, designing, and/or decision-making tool and 1 represents an individual with no experience at all:

____
(1 - 10)

* On a scale of 1 to 5, please give your perception of the <u>realism</u> of the ISLab decision tasks. (Assume 1 = Very Low and 5 = Very High)

____
(1 - 5)

1. Following is a list of the nine possible information items you were able to examine in order to make the investment decisions just completed. Assign a 1 to the dimension you believe was the most important or useful in selecting the appropriate capital investment, 2 to the next most important, and so on. Ties are not permitted.

_______ **NPV**

_______ **Initial Cost**

_______ **Risk**

_______ **Payback**

_______ **Estimation Uncertainty**

_______ **Operating Leverage**

_______ **IRR**

_______ **Annual Net Cash Flow**

_______ **Hurdle Rate**

2. Did you have any major difficulties? Did you record any errors when entering an information request or investment choice? Please explain:

3. Do you think anything should be changed in the way the information was presented (information order, format, etc)?

4. Do you believe there was essential information missing in this decision task? Please explain.

5. Did the varying amount of information affect the way you evaluated each decision task?

6. Was there any attempt on your part to use a consistent approach in requesting and evaluating information (type, order, amount, etc.)?

Evaluate each of the following nine <u>independent</u> situations. Considering all else equal, please indicate which of the two capital investments you would prefer. If needed, refer back to the Instruction Sheet.

1. _____ Investment A: Initial Cost is $210,000

   _____ Investment B: Initial Cost is $180,000

2. _____ Investment A: NPV is $60,000

   _____ Investment B: NPV is $50,000

3. _____ Investment A: Risk is Average

   _____ Investment B: Risk is High

4. _____ Investment A: IRR is 15%

   _____ Investment B: IRR is 14%

5. _____ Investment A: Annual Net Cash Flow is $100,000

   _____ Investment B: Annual Net Cash Flow is $110,000

6. _____ Investment A: Hurdle Rate is 12%

   _____ Investment B: Hurdle Rate is 13%

7. _____ Investment A: Payback is 7 years

   _____ Investment B: Payback is 8 years

8. _____ Investment A: Estimation Uncertainty is Average

   _____ Investment B: Estimation Uncertainty is Low

9. _____ Investment A: Operating Leverage is Very High

   _____ Investment B: Operating Leverage is High

Please answer the following questions regarding your capital budgeting experience. (Not all questions may be applicable for you.)

1. What type of education have you had relevant to capital investment decision making (finance, accounting, etc.)

2. Have you had experience <u>assembling</u> reports to justify capital investments?

What types of capital investments?

General cost range for these investments?

How many years involved in this activity?

3. Have you had experience <u>approving</u> reports to justify capital investments or <u>actually making</u> capital investments?

What types of capital investments?

General cost range for these investments?

How many years involved in this activity?

4. Do you feel you were influenced by any company policies regarding dimension categories or cut-offs? Please explain.

THANK YOU FOR YOUR PARTICIPATION!

** Please write your name on and place all materials (including all instructions, any separate notes you may have made, and the computer disk) into the packet provided. Be sure you have received and signed for any additional monetary compensation before leaving.

APPENDIX B

EXPERIENCED PARTICIPANTS' INSTRUCTIONS AND QUESTIONNAIRE

ISLab Experiment Package Cover Sheet

Experienced Participants

Thank you for your support of research at
The Graduate School of Business Administration,
Michigan State University.

In this packet you should find:
1) ISLab Purpose of Study and set of Instructions
2) ISLab System Instruction Diagram
3) ISLab Questionnaire
4) ISLab 5 1/4" diskette with a floppy disk mailer
5) ISLab 3 1/2" microdisk

This experiment must be run on an **IBM-type** computer. Use the appropriate ISLab disk for your particular disk drive (the other disk will not be used). If your machine is not set to run the disk drive containing the ISLab disk, please switch to the appropriate disk drive, then type "GO" and press [Enter]. Alternatively, you may put the ISLab disk in your boot drive and reboot your machine.

Read your ISLab Purpose of Study and set of Instructions. Respond as requested by the computer. When your session is complete, be sure to complete the questionnaire. Write your name on the disk, the questionnaire, and all other ISLab materials. If you used the 5 1/4" diskette, place it back in the mailer. Place everything into the addressed mailing packet (including the floppy disk mailer) and either give or mail to the experimenter.

Please try to use the computer to do all your decision-making work. If you feel you must make notes or calculations outside of the computer, please include your notes and calculations with the other ISLab materials.

If you have any questions or problems, please contact Monte Swain at MSU's Department of Accounting, (517) 355-7486.

ISLab Pre-Test Instructions

Experienced Participants

ISLab

PURPOSE OF THE STUDY

The purpose of this study is to gain systematic knowledge of the capital investment decisions process. While you are performing the task, the computer will record your selections. Analysis of this data will provide a basis for the development of a detailed descriptive model of capital investment decision making. The model in turn will provide a basis for the development of computer-based decision aids to assist company management responsible for similar decisions. This study should take about one hour to complete.

The aggregated information gathered from this study will be available for your inspection and possible use. All individual information gathered will be kept strictly confidential. At the end of the experiment, you indicate your voluntary agreement to participate by completing and returning the questionnaire attached to this instruction sheet.

INSTRUCTIONS

I. SITUATIONAL ASSUMPTIONS

Assume you are a manager for a large company in need of modernizing a significant segment of the production process. In each of the following decision situations, there are various numbers of investment alternatives available, each requiring a significant expenditure. All investments have an expected life of 10 years. The cost of each investment is within the company's budget constraints. Your task will be to select <u>one</u> and only one capital investment <u>in each situation</u>.
Your company's current need to update its production process and the significant cost to acquire any of the alternatives considered makes the tasks a rather significant investment decision. You should use as much time and information as you feel is <u>necessary</u> for making your decision. Use the computer for all information needs, i.e., please do not make notes to yourself on a separate piece of paper.

II. DECISION SITUATIONS

There are six <u>independent</u> decision situations. In each decision situation you are to choose one capital investment from a set of possible alternatives. Each investment will be represented by various items of information. Additional explanation of each information item is found at the end of these instructions. The information is both quantitative and qualitative in nature. The quantitative data will be given in its natural numerical form (dollars, percentages, etc). Qualitative data will be represented on a five-point scale ranging from Very Low to Very High:

(1) Very low (2) Low (3) Average (4) High (5) Very High

Considerable care was taken to make sure that these capital budgeting situations use information typical of similar investment decisions in industry.

III. THE SYSTEM

The system you will interact with to gather information for the task has three parts:

1. An automatic demonstration
2. A hands-on practice decision situation
3. The six actual decision situations

A. The Automatic Demonstration

A series of steps will be displayed that show how the program operates. This is the same sequence of steps you will be using to make your selections. In the demonstration, the task is to choose a potential employee to hire based on information about GPA, experience, desired salary, and self-motivation (referred to as dimensions). Do not make entries. In this demonstration, the computer will make all entries for you.

Use the attached System Instruction Diagram to follow the automatic operations of the computer. Upon completion of the automatic demonstration you will be prompted to either run another demonstration or to start the sample decision. You may repeat the demonstration if desired.

B. The Sample Decision

In the sample decision, the task again is to select an employee to hire. This time you should respond to the prompts on the screen. All of the steps are the same as described above.

Upon completion of a sample decision, you may either repeat the sample or start the actual decisions.

C. The Actual Decisions

There are six independent decision situations. As described earlier, your task will be to select one capital investment alternative in each decision situation. The sequence of entries is the same as in the samples and the summary screen (the F1 key) is available as described in the System Instruction Diagram. If you make a mistake when selecting an investment, please indicate on the questionnaire.

At the conclusion of the task, be sure to complete the attached questionnaire.

IV. EXPLANATION OF DIMENSIONS

NPV - Net Present Value. A summation of the investment's discounted cash flows and initial cost using the hurdle rate appropriate for this investment type.

Initial Cost - The total cost of purchase, including transportation and set-up costs.

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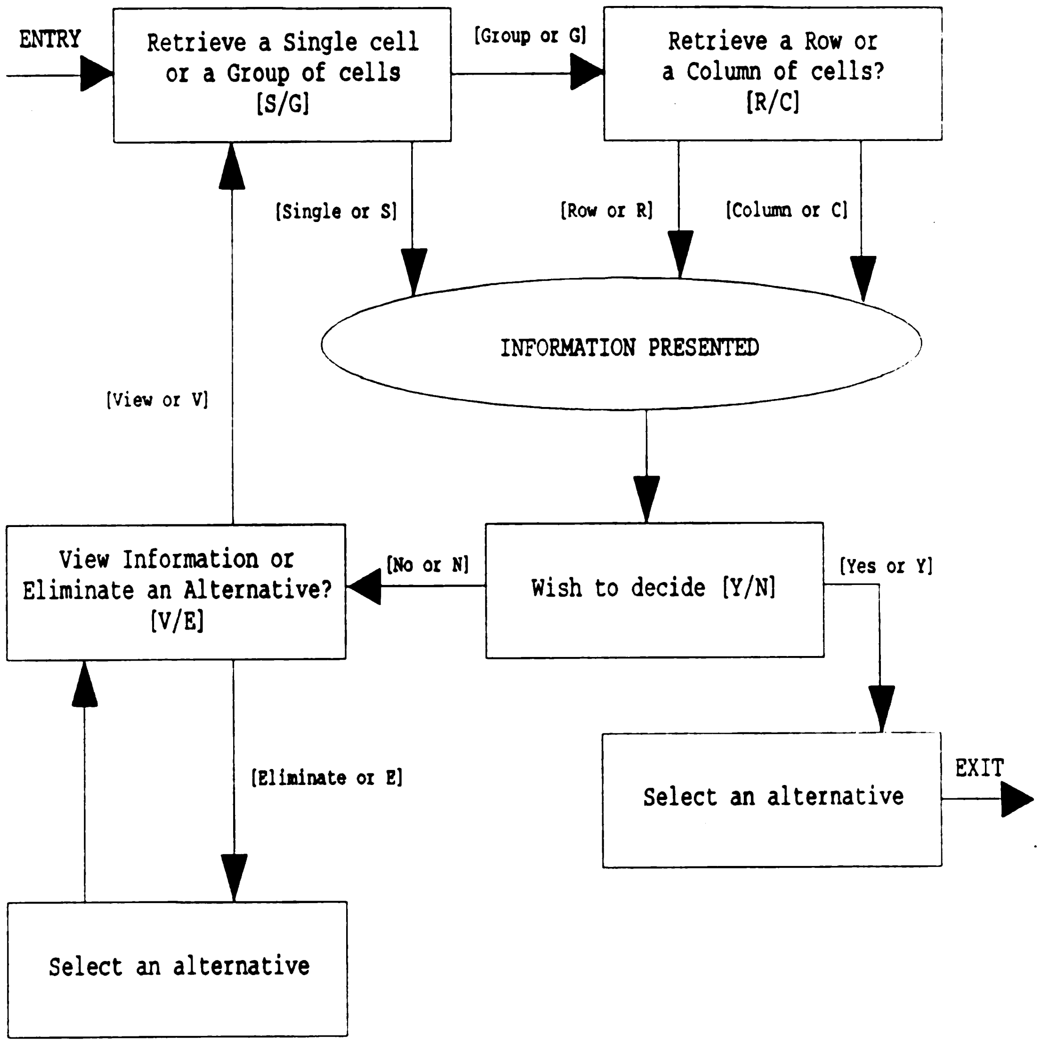
ISLab

SYSTEM INSTRUCTION DIAGRAM



ISLab Post-Test Questionnaire

Experienced Participants

ISLab

QUESTIONNAIRE

Name ____

Company Name ______________________________________

Company Position __________________________________

Female ________ Male ______ Age ______________

Daytime Phone Number ______________________________
(Occasionally, clarification of some responses is required.)

* On a scale of 1 to 10, please rate yourself as an experienced user of microcomputers. Assume 10 represents an individual with significant daily experience using a computer as a programming, designing, and/or decision-making tool and 1 represents an individual who has had no experience using a computer at all:

____
(1 - 10)

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(1 - 5)

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_______ **Hurdle Rate**

2. Did you have any major difficulties? Did you record any errors when entering an information request or investment choice? Please explain:

3. Do you think anything should be changed in the way the information was presented (information order, format, etc)?

4. Do you believe there was essential information missing in this decision task? Please explain.

5. Did the varying amount of information affect the way you evaluated each decision task?

6. Was there any attempt on your part to use a consistent approach in requesting and evaluating information (type, order, amount, etc.)?

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General cost range for these investments?

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3. Have you had experience <u>approving</u> reports to justify capital investments or <u>actually making</u> capital investments?

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How many years involved in this activity?

4. Do you feel you were influenced by any company policies regarding dimension categories or cut-offs? Please explain.

THANK YOU FOR YOUR PARTICIPATION!

** Please write your name on and place all materials (including all instructions, any separate notes you may have made, and the computer disk) into the packet provided.

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