Decision Making Strategies: The Influence of
Task Complexity, Decision Importance,
Decision Maker Impulsivity, and Decision Maker Gender

by

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The effects of decision task complexity, decision importance, and decision maker impulsivity on decision making behavior were studied in this thesis. Measures involving time and acquisition of information were devised as well as specialized measures of decision strategy complexity. Thirty-six subjects classified as either high- or low-impulsives (eighteen male, eighteen female) performed decision tasks involving the selection of the "best" apartment from a group of apartments that were homogeneous with respect to desirability. Decision task complexity was manipulated by increasing the number of apartments from which the subject had to choose. Decision importance was manipulated by changing the reward associated for selecting the best apartment. A theoretical decision strategy selection mechanism, based on a similar mechanism proposed by Christensen-Szalanski (1978), was developed to explain the relationship between the independent variables in this study and decision strategy selection. Results indicated partial support for the theoretical mechanism and highlighted areas for future research.
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Research Objectives

The Research Question

The research question guiding this study is "What effect do problem, decision maker, and decision characteristics have on the selection of decision making strategies?"

The Problem Statement

The problem statement for this research is "What effect do decision task complexity, decision importance, and decision maker impulsivity have on the selection of decision strategies for problems involving the selection of one alternative from a bounded set of known alternatives?" Because the research question is so broad, it must be scoped down to a size suitable for experimentation. The partitioning of the research question may be accomplished in one of two ways.
The first way to partition the research question is to ignore certain parts of the question completely and study the remaining parts in great detail. The problem statement for this type of depth-oriented research might be as follows: "What influence do decision maker characteristics have on the selection of decision making strategies for solving cryptarithmetic problems?" In this case, both problem and decision characteristics would not vary.

The second way to partition the research question is to study one aspect from each part of the research question. In this case, each part of the question is varied, but not to the extent as with the first partitioning method. This type of breadth-oriented research is adopted here because the foundations for a modification to Christensen-Szalanski's (1978) decision strategy selection mechanism are being laid.

The variables of task complexity and decision importance were chosen for two reasons. First, the variables have been studied extensively in the decision making literature. Second, the modifications made to Christensen-Szalanski's (1978) decision strategy selection mechanism operate on cost-benefit principles in which both the costs (in terms of mental effort required) of implementing a particular strategy and the benefits of arriving at the "best" solution are considered. Task complexity serves as a convenient method of varying the cost of implementing a strategy and decision importance serves as a convenient method of varying the benefit associated with the "best" solution.

Decision maker impulsivity was chosen as a personality trait after an extensive review of cognitive and personality traits. The main criterion for choosing this as a personality trait was that impulsivity should be related to decision time—one of the main dependent variables in the proposed study.
Hypotheses

Eight hypotheses are tested in this study. Six within-subject hypotheses are associated with task complexity and decision importance. Two between-subject hypotheses are associated with decision maker impulsivity. Dependent variables measured include time and information acquisition measures or variations of these measures.

Hypotheses H1 and H2 involve decision task complexity and apply to all decision tasks. H1 states that *an increase in decision task complexity will result in an increase in decision time.* H2 states that *an increase in decision task complexity will result in a decrease in average amount of information searched per alternative.*

Hypotheses H3 and H4 apply only to high-complexity decision tasks (i.e., decision tasks with ten alternatives), although these hypotheses are also tested for medium-complexity decision tasks (i.e., five alternatives). H3 states that *subjects will initially use less-complex, noncompensatory, alternative-eliminating decision strategies and then switch to more-complex, compensatory, alternative-evaluating decision strategies.* H4 concerns when this switch will occur. Specifically, H4 states that *subjects will use increasingly more-complex decision strategies (i.e., those requiring more information analysis) as a function of the number of remaining alternatives* (i.e., the number not yet eliminated).

Hypotheses H5 and H6 involve decision importance and apply to all decision tasks. H5 states that *increases in decision importance will result in increases in decision time.* H6 states that *increases in decision importance will result in increases in the amount of information searched before making a decision.*

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1 See Methodology section for the operational definition.

The final two hypotheses, H7 and H8, are between-subject hypotheses concerning the relationship between decision maker impulsivity and decision making behavior. H7 states that high-impulsive subjects will have shorter decision times than low-impulsive subjects. H8 states that high-impulsive subjects will search less information before making a decision than low-impulsive subjects.
The following model provides a logical rationale for hypotheses and a viable explanation for phenomena found in the literature. The model underlying the hypotheses set forth in this proposal is a modified version of Christensen-Szalanski's (1978) decision strategy selection mechanism and is founded on Kurstedt, Polk, and Hughes (1989) expansion of the contingency model of decision making advocated by many researchers in the decision making field (Beach and Mitchell, 1978; Christensen-Szalanski, 1978, 1980; Johnson and Payne, 1985; McCallister, Mitchell, and Beach, 1979; Newell and Simon, 1972; Payne, 1976, 1982; Payne, Bettman, and Johnson, 1988; Russo and Dosher, 1983). The contingency model states that the selection of decision strategies is contingent upon characteristics of the problem and of the decision maker. An expanded view of the contingency model, set forth by Kurstedt, Polk, and Hughes (1989), includes characteristics of decision tools used by the manager and characteristics of the decision. An outline of the expanded contingency model will be presented first. The focus will then turn to describing in detail the modified model of Christensen-Szalanski’s (1978) decision strategy selection mechanism.

3 Most of this section is either paraphrased or directly copied from Kurstedt, Polk, and Hughes (1989).
Outlining the Expanded Contingency Model

The contingency model of decision making states that the selection of a decision strategy is contingent upon problem characteristics and decision maker characteristics. Kurstedt, Polk, and Hughes (1989) have expanded this model by adding decision tool characteristics and decision characteristics. However, since the conceptual difference between problem characteristics and decision characteristics has not been effectively clarified in the literature, the addition of a decision characteristics component to the contingency model may be more accurately described as a refinement than as an expansion.

According to Kurstedt, Polk, and Hughes (1989), all characteristics of individual decision making can be divided into three necessary components and one auxiliary component. The necessary components include the problem, the decision maker, and the decision. Decision tools make up the auxiliary component. Figure 1 on page 7 shows the relationship between these components using an input-process-output paradigm. The decision maker receives the problem as input, processes information (with or without the use of decision tools), and outputs a decision. This view of decision making expands on the contingency model of decision making which states the selection of a decision strategy is contingent upon problem characteristics and decision maker characteristics. Kurstedt, Polk, and Hughes (1989) have expanded this model bringing decision tools and decision characteristics into the picture.

Defining the Components

The problem component is divided into two sub-components: decision task and constraints. The
Figure 1. An input-process-output model of individual decision making.
decision task consists of a question or series of questions the decision maker must address and the set of available information external to the decision maker. The constraints are limitations in resources such as time and money available for solving the problem.

The decision maker component is divided into two sub-components: personality and resources. Resources include characteristics such as knowledge, experience, ability, and intelligence. These indicate what the decision maker knows and can do. The personality sub-component determines how the decision maker uses these resources.

The decision component contains a plan for action designed to answer the question or questions set forth in the task. This plan signals the end of the decision making process.

The decision tools component consists of any devices used by the decision maker that aid in the manipulation or storage of data and information. These include everything from complex decision tools such as expert systems to simple pencil-and-paper storage devices.

Relating the Components to Decision Strategies

Among their personal resources, individuals possess a repertoire of decision strategies. These strategies have different accuracy and cost. Accuracy is the likelihood of producing a satisfactory solution. Cost is the mental effort required to implement a strategy. For any given problem, problem constraints and decision tools help the decision maker identify which strategies in his or her repertoire are feasible. For example, some strategies in the repertoire may require too much

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4 For the purposes of this thesis, a decision task must contain a question. Therefore, assembling a bicycle from a set of instructions would not be considered a decision task since, at a macro level, no question is being asked—the individual merely follows prescribed directions. However, deciding when and where to assemble the bicycle would be considered a decision task since a question or questions are being asked.

5 Excluded are those devices which, although available, are not used by the decision maker due to either lack of ability or willingness.
time or the use of unavailable decision tools. The decision maker eliminates these strategies from consideration as being infeasible.

The expected cost associated with each of the feasible strategies is a function of the mental effort required to apply the strategy. This cost is determined by the decision task characteristics, the decision tools, and the decision maker's resources. One major distinction among various decision strategies is the amount of information the decision maker needs to arrive at a decision. Therefore, decision task characteristics, such as complexity (e.g., the amount of relevant information presented in a problem), influence the cost of implementing each strategy. Decision tools serve as information storage and manipulation devices and therefore may reduce the cost of implementing certain strategies. The level of experience with various decision strategies is part of the decision maker's resources. Strategies the decision maker is experienced with tend to be easier to implement (i.e., less costly) than those that are less familiar.

The decision maker's perception of the decision characteristics determines the maximum effort he or she is willing to expend in solving the problem. Decision characteristics such as decision importance, decision reversibility, and accountability of the decision maker (Beach and Mitchell, 1978) describe the decision's context, or the decision environment. Personality characteristics determine the meaning a decision maker places on informational and environmental stimuli. Mental effort may be conceptualized as an energy reserve set aside for solving a particular problem. The size of this reserve depends on the decision maker's perception of the decision characteristics.

The Decision Strategy Selection Mechanism

The theory of decision strategy selection developed in this thesis is a modified version of the cost-benefit strategy selection mechanism presented by Christensen-Szalanski (1978) and is founded on
the expanded contingency model proposed by Kurstedt, Polk, and Hughes (1989). According to Christensen-Szalanski (1978), the decision maker weighs the expected benefits and costs associated with each decision strategy and chooses the one that results in the maximum benefits-to-cost ratio. The assumption that a decision maker will consider costs and expected benefits when selecting a decision strategy is reasonable. However, the assumption that the decision maker will somehow calculate a cost-benefit ratio for each and every decision strategy available does not seem reasonable.

To modify the selection mechanism of Christensen-Szalanski (1978), in place of calculating individual cost-benefit ratios for each strategy, Kurstedt, Polk, and Hughes (1989) introduced the idea of a threshold of mental effort upon which the decision maker will focus. The decision maker will look for the most accurate strategy below the threshold. The threshold may change as effort is expended. The threshold is a “reservoir” of mental effort, so to speak, earmarked for solving a particular problem. Figure 2 on page 11 shows an example of four feasible decision strategies of a person's repertoire placed along a continuum of the mental effort required to apply a strategy to a given problem. Only decision strategies 2, 3, 7, and 11 are feasible out of the available alternatives. The strategies are numbered randomly, without respect to any mental effort requirements. The location of each strategy depends upon task characteristics, decision tools, and the decision maker's resources. The shaded area in Figure 2 on page 11 is the limit on mental effort the decision maker is willing to expend on solving the problem. In this case, the decision maker will select D87. The top of the shaded area represents the threshold, which will change as the decision process proceeds.

Kurstedt, Polk, and Hughes (1989) assume, as do Christensen-Szalanski (1978) and Beach and Mitchell (1978), the more accurate a strategy, the more costly it is to implement. However, Christensen-Szalanski's (1978) selection mechanism ignores the absolute cost of implementing a decision strategy, focusing instead on its cost relative to its expected benefit (i.e., accuracy). The proposed modified selection mechanism focuses on the absolute cost of implementing a strategy relative to the amount of effort set aside in the “reservoir.”
Figure 2. Decision strategy costs and effort willing to expend.
Explaining Decision Making Phenomena

Two decision making phenomena are commonly found in the decision making literature. First, there is a positive relationship between the importance of a decision and the use of analytic decision strategies. Second, when faced with the task of selecting one alternative from a large number of alternatives, decision makers typically use simple, noncompensatory strategies to eliminate alternatives, and then, when only a few alternatives remain, switch to more analytic, compensatory decision strategies. The main difference between noncompensatory and compensatory decision strategies lies in speed versus accuracy tradeoffs. Noncompensatory strategies require little effort or time to implement and have the ability to eliminate alternatives quickly, but at the cost of reduced accuracy. Compensatory strategies, on the other hand, have high degrees of accuracy, but at the cost of increased time and effort.

The Importance Phenomenon

The decision making literature provides a firm foundation for the contention that high-importance decisions lead to the use of analytic decision strategies, whereas low-importance decisions do not. McAllister, Mitchell, and Beach (1979) showed that individuals used more analytic decision strategies when the decision was significant, the decision maker was accountable for the decision, and the decision was irreversible. All three variables influenced importance perceptions of the decision. Christensen-Szalanski (1978) found that individuals used more complex strategies to solve more valuable (i.e., important) problems.

The modified decision strategy selection mechanism accounts for this phenomenon. As stated earlier, the decision maker's perception of the decision characteristics (e.g., importance) determines the maximum amount (threshold) of mental effort he or she is willing to expend on solving the
problem. Furthermore, the decision maker will choose the best feasible decision strategy not exceeding this maximum. In Figure 2 on page 11, this strategy is DS7. Now assume we have the same problem and the same feasible strategies, but that the decision is now very important. In effect, the shaded area shown in Figure 2 on page 11 would be higher. If the decision is important enough, DS2 or perhaps DS11 will be selected. Similarly, if the problem is relatively unimportant, the shaded area would be lower, leaving only the simplest strategy (DS3) available.

The Strategy Switching Phenomenon

The phenomenon of switching from less-complex, alternative-eliminating (i.e., noncompensatory) decision strategies to more-complex, alternative-evaluating (i.e., compensatory) decision strategies during the decision process is also well-documented in the literature. Lussier and Olshavsky (1979), for example, showed that when more than three brands of typewriters (i.e., alternatives) were presented, subjects first used noncompensatory strategies to reduce the number of alternatives and then switched to compensatory strategies when only a few alternatives remained. Similarly, Bettman and Park (1980) found that subjects used alternative-eliminating strategies such as elimination-by-aspects (Tversky, 1972) in early phases of decision making, switching to alternative-evaluating strategies such as weighted compensatory in later phases.

Assuming decision makers strive to use the most accurate strategy available not exceeding the maximum effort they are willing to expend, the modified decision strategy selection mechanism accounts for this phenomenon. This requires examining the effects that using one strategy has on the relative costs of the using the other feasible strategies.

Noncompensatory strategies, such as elimination-by-aspects (Tversky, 1972) or lexicographic (See Payne, Bettman, and Johnson, 1988 for a full description.), are characterized by their ability to quickly eliminate alternatives with little effort expenditure. This means that only a small amount
of effort is drained from the mental effort reservoir while the number of remaining alternatives is greatly reduced. However, noncompensatory strategies are also characterized by relatively low accuracy rates compared to compensatory strategies, such as expected utility. As noncompensatory strategies eliminate alternatives, the effort required to apply any of the feasible strategies to the rest of the problem decreases as a function of the number of remaining alternatives. For example, applying a compensatory strategy to five alternatives requires about half the effort of applying that same strategy to ten alternatives.

When noncompensatory decision strategies are employed, the expected cost associated with each available decision strategy decreases faster than the effort expenditure. This means that the positions of the decision strategies on the mental effort continuum drop faster than the threshold of mental effort the decision maker is willing to expend. Figure 3 on page 15 illustrates this point. At some point, the expected cost associated with a more accurate strategy than the one currently being employed may fall below the amount of effort left in the reservoir. According to the modified decision strategy selection mechanism, when this occurs the decision maker will switch to the new strategy.
Figure 3. Reduction over time of strategy cost and effort reservoir.
Literature Review

Decision Task Complexity

Distinguishing Between Tasks and Decision Tasks

Before decision task complexity is reviewed, a decision task is differentiated from a task. A task can be defined as an instruction or set of instructions perceived (by the individual who will perform the task) as a series of well-defined actions that will lead to known outcomes. A decision task includes one or more questions which must be answered to reach the desired outcome. To an experienced mechanic, the phrase "change the oil" is perceived as a set of well-defined actions and is therefore considered a routine task. For the novice, however, this is a decision task since no such set of well-defined actions is perceived and since questions concerning which procedures to take and in which order must be answered before the desired outcome can be reached.

This distinction is evident in Wood's (1986) conceptualization of task complexity. He defines task complexity in terms of the behaviors individuals typically exhibit when performing the task and in
terms of the ability requirements of the task. This implies two assumptions that, although appropriate for tasks, are too restrictive for decision tasks. First, when complexity is defined in terms of "typical" behaviors, one must assume most or all individuals will exhibit the same set of behaviors. For many decision tasks, however, no set of typical behaviors exist. Newell and Simon (1972) demonstrated that individuals do not solve problems per se, but rather they solve their internal representations (i.e., perceptions) of those problems. Since these representations may vary substantially from one person to another, so may the resulting behaviors. Second, defining complexity in terms of ability requirements assumes there are only one or a few "right" ways to perform the task. Ability requirements, beyond a rudimentary level, are not an inherent part of a decision task. The decision task of choosing one alternative from a set of competing alternatives, for example, may be performed many ways. One person may evaluate all the information about all the alternatives using an expected utility model to determine the optimal solution. Another, however, may simply look at a small subset of information and select the first alternative meeting some minimum criteria. The ability requirements of the first selection method (i.e., some knowledge of utility theory) differ greatly from those of the second selection method. However, since no method is dictated by the problem, no ability requirements can be determined.

Defining the Construct for Decision Task Complexity

In his review of the literature, Campbell (1988) identified three approaches to defining decision task complexity: complexity primarily as a subjective psychological experience, complexity as a person-task interaction, and complexity as objective characteristics.

Complexity defined primarily as a psychological experience emphasizes individuals' subjective reactions to task stimuli. Campbell (1988) cited literature in which complexity was equated with enrichment (Pierce and Dunham, 1976) and with challenge (Taylor, 1981). Klein and Cooper (1981) defined a decision task's complexity in terms of decision making loads placed on the indi-
idual. This view of decision task complexity does not ignore objective decision task characteristics. Rather, it considers them indirectly by focusing on the perceptions individuals have of these characteristics. In this framework, complex decision tasks are characterized by autonomy, variety, feedback, and identity (Ganster, 1980) and are seen as stimulating (Taylor, 1981).

Complexity defined as a person-task interaction acknowledges the importance of decision task characteristics as well as capabilities of the individual performing the task. This view of decision task complexity was implicit in work by March and Simon (1958) who discussed complexity relative to the capability of the individual performing the task. Frost and Mahoney (1976) discussed goal difficulty level (i.e., decision task complexity) in terms of the degree to which an individual draws on his or her skills and on individual differences in skill level relevant to the decision task. Campbell (1988) cited literature suggesting that decision task complexity varies as a function of the task's mode of representation (Hammond, 1986; Stock and Watson, 1984; Tversky and Kahneman, 1981). Hammond (1986) pointed out the distinction between making judgments from memory and making judgments when past information is displayed. Stock and Watson (1984) found that accountants performed a bond rating task better when their judgments were based on schematic faces (e.g., smiley faces) used to represent numerical data rather than on the data itself. Tversky and Kahneman (1981) found that probabilistic-based decisions vary depending on how the probabilities are presented, even though the probabilities are objectively identical.

Complexity defined primarily as a function of objective decision task characteristics is summarized under three categories: information characteristics, path characteristics, and constraint characteristics. (See Table 1 on page 19.)

Information characteristics refers to aspects of the information used to solve a problem and the interrelationships between various pieces of information. Payne (1976) defined decision task complexity in terms of the number of alternatives and the number of dimensions per alternative. Schroder, Driver, and Streufert (1967) also included rate of information change (an indicator of uncertainty) as a determinant of decision task complexity. March and Simon (1958) suggested that
Table 1. Problem Complexity as a Function of Objective Characteristics: Adapted from Campbell (1988).

Information Characteristics
- information load, diversity, and rate of change (Schroder, Driver, and Streufert, 1967)
- information interrelationships (Steinmann, 1976)
- multiple alternative with multiple attributes (Payne, 1976)
- unknown/uncertain alternatives or outcomes (March and Simon, 1958)

Path Characteristics
- multiple path-goal connections (Terborg and Miller, 1978)
- inexact means-ends connections (March and Simon, 1958)

Constraint Characteristics
- multiple/uncertain performance criteria (Latham and Yukl, 1975)
- constraints that need to be satisfied (Earley, 1985)
- interrelated and conflicting sub-tasks (Campbell, 1984)
the novelty of a stimulus (i.e., problem situation) at least partially determines problem complexity, since relatively novel stimuli "will evoke problem-solving activity aimed initially at constructing a definition of the situation and then at developing one or more appropriate performance programs" (p. 140). Steinmann (1976) suggested that decision task complexity can be manipulated by varying the following: the number of cues (i.e., total amount of information), cue intercorrelations, cue validity and problem predictability, relationship between cues (i.e., linear vs. curvilinear), cue and criterion variability, and the principle or rule underlying information integration. Decision task complexity changes as information characteristics change because of the influence these changes have on the information processing requirements placed on the decision maker.

Path characteristics refers to the number of methods, real or apparent, leading to a solution and the degree to which these methods are easily determined (March and Simon, 1958, pp. 148-149; Terborg and Miller, 1978). An increase in the number of paths to a solution increases decision task complexity under the following conditions: (a) when only one path leads to the solution although many paths appear as possibilities, and (b) when the individual is required to find the best path among the alternatives (Campbell, 1988). Similarly, a decrease in ease of path determinability leads to an increase in decision task complexity. In both cases, this increase results from increased information processing requirements needed to select the appropriate decision strategy.

Constraint characteristics refers to characteristics of the conditions a problem solution must satisfy. Complexity arises from the number of criteria that must be satisfied and the relationships between them. Latham and Yukl (1975) discussed decision task complexity in terms of the number of performance dimensions and the uncertainty involved in selecting them. This complexity arises from the additional information processing required to determine those performance criteria a solution should satisfy. Earley (1985) manipulated decision task complexity in a class scheduling task by imposing three additional decision rules on subjects in the high-complexity condition. Similarly, Campbell (1984) defined a complex decision task as having several interrelated and conflicting elements to satisfy. Although the decision rules were provided (unlike the Latham and Yukl, 1975

Literature Review

20
study), the necessity that solutions satisfy additional constraints placed additional information processing requirements on the subjects, thereby increasing complexity.

Supporting the Decision Task Complexity Hypotheses

Two sets of hypotheses concerning the effect of decision task complexity on individual decision making were outlined earlier. The first set hypothesizes that an increase in initial task complexity would lead to: (H1) an increase in decision time and (H2) a decrease in average percent of information searched per alternative. Table 2 on page 22 summarizes literature supporting these hypotheses. In each case that decision time and/or average percent of information searched per alternative were measured, H1 and H2 were supported.

The second set of hypotheses were addressed to those problems high in initial decision task complexity (i.e., ten alternatives). H3 states that subjects will initially use less-complex, noncompensatory, alternative-eliminating decision strategies and then switch to more-complex, compensatory, alternative-evaluating decision strategies. Furthermore, H4 states this switch will occur as a function of the number of remaining alternatives (i.e., those not yet eliminated) and decision importance.

Lussier and Olshavsky (1979) examined the relationship between decision task complexity and decision strategy selection. Complexity was manipulated by varying the number of alternatives (three, six, or twelve typewriters) and number of attributes per alternative (five, ten, or fifteen). They found that seven out of nine subjects in the six-alternative condition and nine out of nine subjects in the twelve-alternative condition used a two-step decision strategy. The first step involved alternative-eliminating, noncompensatory decision strategies. The second step involved alternative-evaluating, compensatory decision strategies. Based on verbal protocols of the twenty-seven subjects, Lussier and Olshavsky (1979) found that the number of alternatives on display largely determined whether
<table>
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<th>AUTHOR(S)</th>
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<th>MANIPULATION OF COMPLEXITY</th>
<th>INCREASES IN INITIAL COMPLEXITY RESULTED IN...</th>
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<tbody>
<tr>
<td>Polley</td>
<td>1970</td>
<td>2 or 8 dimensions per alternative</td>
<td>INCREASE</td>
</tr>
<tr>
<td>Jacoby, Speller, and Kotn</td>
<td>1974</td>
<td>2, 3, or 12 brands with either 2, 4, or 6 items per brand</td>
<td></td>
</tr>
<tr>
<td>Campbell and Ezek</td>
<td>1976</td>
<td>1, 2, or 3 moves to achieve checkout</td>
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<tr>
<td>Park</td>
<td>1976</td>
<td>small or large number of evaluative criteria</td>
<td></td>
</tr>
<tr>
<td>Payne</td>
<td>1976</td>
<td>2, 6, or 12 alternatives with 4, 8, or 12 dimensions per alternative</td>
<td></td>
</tr>
<tr>
<td>Lassar and Olohezky</td>
<td>1979</td>
<td>3, 6, or 12 brands with either 5, 10, or 15 attributes per brand</td>
<td>DECREASE</td>
</tr>
<tr>
<td>Olohezky</td>
<td>1979</td>
<td>3 or 12 alternatives with 6 or 15 attributes per alternative, or dichotomous or multi-nominal attributes' values</td>
<td>DECREASE</td>
</tr>
<tr>
<td>Huber</td>
<td>1980</td>
<td>1 or 5 alternatives with 3 or 6 dimensions per alternative</td>
<td></td>
</tr>
<tr>
<td>Smith, Mitchell, and Beach</td>
<td>1982</td>
<td>requirement to compute either 2 or 5 specific measures for 5 investment alternatives.</td>
<td></td>
</tr>
<tr>
<td>Ehrley</td>
<td>1985</td>
<td>no criteria or 3 criteria in the form of rule(s) that a decision must satisfy</td>
<td></td>
</tr>
<tr>
<td>Huber</td>
<td>1985</td>
<td>25 x 25 maze with a requiring a minimum of 23 moves or a 42 x 42 square maze requiring a minimum of 83 moves</td>
<td>INCREASE</td>
</tr>
<tr>
<td>Johnson and Payne</td>
<td>1985</td>
<td>2, 4, or 8 alternatives each with 2, 4, or 8 possible outcomes</td>
<td></td>
</tr>
<tr>
<td>Onsjust, Hastie, and Revelle</td>
<td>1985</td>
<td>2, 4, 8, or 12 alternatives with 2, 4, 8 or 12 attributes per alternative</td>
<td>INCREASE</td>
</tr>
<tr>
<td>Campbell and Gingrich</td>
<td>1986</td>
<td>computer programs requiring standard completion times of 45 hours or less or more than 40 hours</td>
<td></td>
</tr>
<tr>
<td>Luriechev and Moschkovich</td>
<td>1988</td>
<td>either 2 or 4 alternative-evaluation categories</td>
<td></td>
</tr>
<tr>
<td>Navinshah and Vicker</td>
<td>1988</td>
<td>3 objective or a 6 objective problem</td>
<td>INCREASE</td>
</tr>
<tr>
<td>Paquette and Kida</td>
<td>1988</td>
<td>2, 5, or 9 alternative business firms</td>
<td>INCREASE</td>
</tr>
</tbody>
</table>
subjects used a one-step or two-step process. Although this number varied across subjects, subjects who were initially presented with more than three alternatives generally used a two-step strategy. In a similar study, Olshavsky (1979) found that seventeen out of twenty subjects used a multi-stage strategy decision strategy when initially presented with twelve alternatives. The results of these studies support hypotheses H3 and H4.

Other evidence supporting H3 and H4 was provided by Bettman and Park (1980) who examined the relationship between decision making phase and decision task complexity. They found that subjects engaged in more attribute processing than alternative processing in early phases of a decision. Attribute processing is indicative of alternative-eliminating decision strategies. Furthermore, they found a greater occurrence of noncompensatory decision strategies such as elimination-by-aspects in early phases of the decision and a greater occurrence of compensatory decision strategies in later phases.

**Decision Importance**

**Defining the Construct for Decision Importance**

Webster's Ninth New Collegiate Dictionary (1989) defines *important* as "marked by or indicative of significant worth or consequence" (p.605). This implies that the importance of an event is related to the magnitude of the consequences resulting from that event. A decision, therefore, can be said to be important if its consequences are of relatively large magnitude. Note that no mention of directionality of consequences is included in this definition. That is, both positive and negative consequences of a decision make that decision important if the consequences are of significant
magnitude. I define Decision Importance, therefore, as the magnitude of the consequences the decision maker perceives will result from a decision.

This conceptualization of importance is similar to Vroom's (1982) concept of valence in his book about work and motivation. Valence refers to affective orientations toward (i.e., how you feel about) particular outcomes. An outcome has positive valence when the person prefers attaining it to not attaining it (i.e., reward) and has negative valence when the person prefers not attaining it to attaining it (i.e., punishment). Vroom (1982) emphasized the difference between the valence of an outcome and its actual value. Valence refers to the anticipated satisfaction associated with the attainment of an outcome while value refers to the actual satisfaction an outcome provides. He notes that the strength of a person's desire for (or aversion to) a particular outcome stems not from its intrinsic properties, but rather from the anticipated satisfaction associated with it. The perceived nature of importance was emphasized by Cragin (1983) who stated, "the single concept upon which virtually all theorists and researchers employing the importance construct seem to agree...[is]...importance is a perception" (p. 262).

Supporting the Decision Importance Hypotheses

Theoretical support. Two hypotheses concern the impact of decision importance on decision making behavior. The hypotheses state that as decision importance increases, decision time will increase (H5) and the amount of information searched will increase (H6). This is explained by the relationship between decision importance and the effort the individual is willing to expend to solve a problem. Humphreys and Revelle (1984) discussed the relationship between motivation and the allocation resources. They noted that there are costs associated with the allocation of these resources and that the individual may withhold resources unless the benefits for doing well on a task (i.e., decision importance) are increased. Williams and Teasdale (1982) adopted this view in their discussion of the relationship between effort and performance incentives in terms of learned
helplessness. They portrayed the cost associated with expending effort to solve a problem as a "negative incentive." This "negative incentive" must be balanced or justified by the "positive incentive" associated with successful performance of a task (i.e., decision importance).

The theoretical support for hypotheses H5 and H6 lies in the interpretation of "resources" and "effort." Assuming that an individual will not increase the intensity with which he or she attacks a problem, then expending more effort on a problem or allocating more resources to it can only be achieved by spending more time with that problem, processing more information.

**Empirical Support.** Christensen-Szalanski (1978) developed a decision strategy selection model based on cost-benefit principles. In a series of experiments, he manipulated the value (or benefit) of making a correct decision (i.e., decision importance) to determine its effect on decision strategy selection. This was done by assigning point values for particular problems, ranging from 10 to 500 points, which the subject could earn by providing a correct decision. The subjects were paid at the end of the experiment based on the number of points they earned. The results indicated that subjects took longer to decide on problems with higher point values and used more complex decision strategies. Subjects were required to choose a strategy from a set of 8 strategies which differed primarily in the amount of information needed to implement the strategy. Therefore both hypotheses, H5 and H6 were supported.

McAllister, Mitchell, and Beach (1979) tested the effects of task significance, decision maker accountability, and decision reversibility on the selection of decision strategies. In the model of decision strategy selection set forth in this proposal, these three variables come under the general heading of "decision importance" since each (theoretically) should increase the perceived magnitude of the effect the individual expects will result from the decision (i.e., valence). For the first two out of three experiments carried out by these authors, experimental manipulations were administered through alterations made to organizational case studies. Significance was manipulated by changing the impact a decision would have on the financial status of a company (e.g., affects either 80% or 10% of available funds). Accountability was manipulated by casting the decision as the sole re-
sponsibility of the subject or merely as a recommendation to be reviewed by others. Reversibility was manipulated by either allowing the character (played by the subject) to change his or her mind or by making the decision permanent. The subjects were required to choose one decision strategy from a set of four decision strategies, differing in terms of the amount of computation and analysis required, to apply to a given case.

The results of experiments one and two indicated that subjects chose more analytic strategies for significant cases relative to insignificant ones, for cases the decision maker was accountable for relative to ones he or she wasn’t, and for cases that were irreversible relative to ones that were reversible.

In experiment three, significance was manipulated by informing the subjects that either (a) the experiment was the result of a long period of experimental work and was more likely to lead to important results, or (b) that the experiment was a pilot study supported by a small group of local consultants and would have little meaningful impact. Accountability was manipulated by telling the subjects either (a) they would be required to defend their answers in front of a small group of their peers, or (b) their answers would simply be reviewed. Decision reversibility was manipulated by either (a) allowing subjects to change their decisions at the end of the research period, or (b) making their initial decisions final. The results indicated that subjects used more analytic strategies and spent more time on decisions they were accountable for. There were no significant differences in decision time or strategy selected for the significance and reversibility manipulations. The results of these three experiments support hypotheses H5 and H6.

Billings and Scherer (1988) manipulated decision importance for tasks involving either judgment or choice. Only those results concerning tasks involving an explicit choice will be discussed, since they are analogous to the experimental tasks presented in this proposal. Subjects made decisions on candidates for residence hall advisors based on six dimensions of information about each candidate. Subjects in the high-decision-importance condition were told that policy makers in the Office of Residence and Dining Halls were going to use the results of the experiment in deciding
what type of information would be gathered on future applicants and that those subjects whose responses most closely matched those of the "experts" would be included in the actual resident advisor selection process. Subjects in the low decision importance condition were told that the experiment was simply a test of decision making theories and that there were no right or wrong answers and no correct decision strategy. No mention was made of the Office of Residence and Dining Halls. Results indicated that subjects searched more information in the high decision importance conditions. This supports hypothesis H6.

Smith, Mitchell, and Beach (1982) used investment analysis problems to test further extensions on the cost-benefit mechanisms proposed to underlie decision strategy selection. (See Beach and Mitchell, 1978 and Christensen-Szalanski, 1978 for the original work.) Task significance (i.e., decision importance) was manipulated by altering the amount of money a person could earn for a given problem. For each problem in the low-task-significance condition, the subject could earn a maximum of $1. For each problem in the high-task-significance condition, the subject could earn a maximum of $4. The results indicated no statistically significant effects of task significance on decision strategy selection. The authors believed this was due in large part to an inadequate manipulation of task significance. In fact, the manipulation check showed that the difference across task significance conditions was not perceived as being significant. The authors' review of subject responses to the manipulation check suggested that both task significance conditions were perceived as less than average. It is also important to note that subjects in this study were first year MBA students enrolled in the Graduate School of Business at the University of Washington. Since money was used to manipulate task significance, one would expect differences in the perceived value of money between graduate students and undergraduate students. That is, although the subjects in this study did not differentiate between the $1 and $4 payoff levels, subjects such as undergraduate or high school students may perceive a marked distinction between these two payoff levels.
Impulsivity

Defining the Construct of Impulsivity

In Jackson’s (1984) Personality Research Form (PRF), a high-impulsive individual “tends to act on the ‘spur of the moment’ and without deliberation; gives vent readily to feelings and wishes; speaks freely; may be volatile in emotional expression” (p. 7). Furthermore, Jackson (1984) defined impulsivity by the following adjectives: “hasty, rash, uninhibited, spontaneous, reckless, irrepressible, quick-thinking, mercurial, impatient, incautious, hurried, impulsive, foolhardy, excitable, and impetuous” (p. 7).

Barrat (1987, 1985) defined impulsivity in terms of three subtraits: motor impulsiveness, cognitive impulsiveness, and non-planning impulsiveness. Motor impulsiveness involves acting without thinking and, according to Barrat (1987, 1985) is similar to Eysenck’s (1977) concept of “impulsiveness narrow.” Cognitive impulsiveness involves making quick cognitive decisions and is similar to the liveliness factor in Eysenck and Eysenck’s (1977) concept of “impulsiveness broad.” Non-planning impulsiveness involves the lack of a “future” orientation; a lack of planning ahead.

Gerbing, Ahadi, and Patton (1987) defined impulsivity as a “tendency to respond quickly to a given stimulus, without deliberation and evaluation of consequences” (p. 357). This definition of impulsivity is similar to Barrat’s (1987, 1985) motor impulsiveness.
Supporting the Impulsivity Hypotheses

Barrat (1987) pointed out that global measures of impulsiveness are related to performance on perceptual-motor tasks such as reaction time and visual tracking, cognitive measures such as time production (i.e., performing a task for a specified length of time), and psychophysiological measures concerning reaction to visual stimuli (e.g., visually-evoked potentials). Notably missing from this list is evidence linking impulsivity to decision making. Therefore, evidence to support the hypotheses laid out in this thesis concerning impulsivity will only be theoretical in nature (as opposed to empirical).

Ainslie (1975) listed three reasons offered by philosophy and science why people behave impulsively, which he defined as choosing "the poorer, smaller, or more disastrous of two alternative rewards even when [one is] entirely familiar with the alternatives" (p. 463). These reasons are:
In seeming to obey impulses, people do not knowingly choose the poorer alternative but have not really learned the consequences of their behavior. Socrates said something like this. Those who hold this kind of theory prescribe education or "insight" as the cure for impulsiveness.

2. In obeying impulses, people know the consequences of their behavior but are impelled by some lower principle (the devil, repetition compulsion, classical conditioning) to act without regard for differential reward. Those who hold this kind of theory prescribe some means of exercising the lower principle, such as abreaction [a means of releasing repressed emotion by acting out] or desensitization.

3. In obeying impulses, people know the consequences of their behavior, but their valuation of the consequences is innately distorted so that imminent consequences have a greater weight than remote ones. Those who hold this kind of theory prescribe devices that serve to commit future behavior to courses decided on well in advance.

Ainslie (1975) supported the third reason, rejecting the first two after reviewing the literature. This support was due to evidence he found in the literature which suggested that the effectiveness of delayed reward declines such that a small reward received early may be preferred over larger rewards received after a long delay.

If Ainslie (1975) is correct, then this would add theoretical support for hypotheses H7 and H8 which state that high-impulsive subjects will decide more quickly and search less information before making a decision. That is, for the high-impulsive individual, the value of a reward diminishes as the delay for receiving that reward increases. Therefore, the high-impulsive individual should strive to solve the problem as quickly as possible which, in turn, means that less information can be searched. Further theoretical support for H7 was provided by Revelle (1987) who, after reviewing studies of the effects of personality and motivation on cognitive performance, concluded that one difference between low impulsives and high-impulsives was that high-impulsives are more biased toward speed of performance relative to accuracy.

Selecting an Appropriate Measure of Impulsivity

Gerbing, Ahadi, and Patton (1987) listed most of the widely used impulsivity measures. These fall into three categories: self-report measures, behavioral measures, and measures involving time. Self-report measures exist either as individual scales on larger personality tests, or as specialized tests.
in and of themselves. Scales include the Personality Factors Questionnaire (16PF) Impulsivity scale (Cattell, Eber, and Tatsuoka, 1970); the Guilford-Zimmerman Temperament Survey (GZTS) Restraint scale (Guilford, Guilford, and Zimmerman, 1978); the Personality Research Form (PRF) Impulsivity scale (Jackson, 1984); and the impulsivity scale from the EASI Temperament Survey, Version III (Buss and Plomin, 1975). Specialized self-report measures of impulsivity include the I-7 (Eysenck, Pearson, Easting, and Allsopp, 1985) and the I-5 (Eysenck and Eysenck, 1977), and the Barrat Impulsivity Scale, Version 10 (BIS-10) (Barrat, 1985). The most widely used behavioral measure purported to estimate impulsivity, according to Gerbing, Ahadi, and Patton (1987) is Kagan's (1966) Matching Familiar Figures Test. Measures involving time include Simple Reaction Time and Time Perception (Barrat and Patton, 1983).

The measure selected for the proposed research is the impulsivity scale from Jackson’s (1984) Personality Research Form. This 16 item True-False questionnaire was chosen for two reasons. First, the test is easy to administer and grade, and requires only a few minutes to complete. Because only high-impulsives and low impulsives will be studied, many individuals who take the test will not be accepted into the study. For this reason, a simple, short test is imperative. Second, the psychometric rigor with which the PRF was constructed is well documented (Jackson, 1984), with careful attention being paid to validity and reliability throughout the construction process.6

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6 For a detailed discussion concerning the construction and evaluation of the PRF, see Jackson (1984, pp. 27-59).
Methodology

Experimental Design

Introduction

The experimental design for this study was a $3 \times 3 \times 2 \times 2$ mixed-factor, full-factorial design. (See Figure 4 on page 34.) The presentation of the experimental manipulations accomplished using a decision task involving the selection of one apartment (described along seven dimensions such as rent, noise level, etc.) from a set of apartments. Each set of apartments was displayed on a touch screen, a device which recognizes the location of a touch made to the surface of the screen. The values of each of the seven dimensions of the apartments were initially hidden under a matrix of asterisks displayed on the screen. The subject "uncovered" the value of a dimension for a particular apartment by touching the appropriate asterisk. When the subject touched another asterisk, the previous value was hidden again by an asterisk. In this way, if a subject forgot a previously uncovered value, he or she would have to uncover it again to obtain that value. The dependent variables consisted of measures taken by a computer via inputs made to the touch screen during
decision task performance and measures taken via the keyboard after the completion of each decision task.

**Independent Variables**

Problem complexity, a within-subjects variable, was manipulated by changing the number of apartments presented to the subject at the beginning of each trial. The low-complexity condition consisted of two apartments, the medium-complexity condition consisted of six apartments, and the high-complexity condition consisted of ten apartments. In all cases, seven dimensions were used to define an apartment. Each dimension had three values. All dimensions with all possible values are shown in Table 3 on page 35.

*Decision Importance*, a within-subjects variable, was manipulated by changing the reward amount for choosing the "correct" alternative. The "correct" alternative was derived from data collected in a pre-test phase of the study and will be discussed in detail later. The reward levels were, $0.25 for the low-importance condition, $0.75 for the medium-importance condition, and $2.00 for the high-importance condition.

*Decision Maker Impulsivity*, a between-subjects variable, was measured using the impulsivity scale in the Personality Research Form (Form E) developed by Jackson (1984). This scale is a 16 item, true-false, self-report questionnaire. The 18 individuals scoring the lowest on this test were placed in the low-impulsive group and the 18 highest scorers were placed in the high-impulsive group.

*Gender*, a between-subjects variable, was measured by self-report on a general demographics form.
Figure 4. The experimental design.

MALES

FEMALES
Table 3. Each dimension consists of three values.

<table>
<thead>
<tr>
<th>DIMENSION</th>
<th>LEVELS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rent</td>
<td>High, Average, Low</td>
</tr>
<tr>
<td>Bedroom Size</td>
<td>Large, Medium, Small</td>
</tr>
<tr>
<td>Liv/Din Room Size</td>
<td>Large, Medium, Small</td>
</tr>
<tr>
<td>Cleanliness</td>
<td>Good, Average, Poor</td>
</tr>
<tr>
<td>Noise Level</td>
<td>High, Medium, Low</td>
</tr>
<tr>
<td>Laundry Facilities</td>
<td>Apartment, Complex, None</td>
</tr>
<tr>
<td>Distance to Campus</td>
<td>30 min, 15 min, 5 min</td>
</tr>
</tbody>
</table>
Control Variables

To reduce variance in collected data due to sources other than those of interest, time pressure and age, experience, and problem type were controlled. Christensen-Szalanski (1980) demonstrated that limits on time allowed to solve a problem influenced decision strategy selection. Therefore, since time pressure was not one of the independent variables in this study, no time limit was imposed on the subjects. Age, experience, and problem type variables were controlled through subject selection and pre-test procedures and will be discussed in later sections.

Dependent Variables

All hypotheses were tested using two main dependent measures: time and touch screen inputs. The following is an exhaustive list of dependent measures used to test the hypotheses:

- Decision Time was the interval of time beginning when a set of alternatives is initially displayed and ending when all alternatives but one have been eliminated. This value was corrected to reflect the amount of time spent recovering from inadvertent, detected errors. These errors were misinterpreted inputs to the Touch Screen which were handled and corrected by the control program.

- Amount of Information Searched was the total number of touch screen inputs, corrected to reflect inadvertent, detected errors.

- Average Amount of Information Searched per Alternative was the Amount of Information Searched divided by the number of alternatives presented at the beginning of a trial.

7 See Experimental Apparatus section for details on the touch screen.
Decision Strategy Complexity Rating was an index of the overall complexity of decision strategy used in an elimination period based on the average number of dimensions considered per alternative for a given decision strategy.\(^8\)

Manipulation Checks

To validate the complexity and importance manipulations, two manipulation checks were devised. Each check consisted of a question and a nine-point, bipolar, semantic differential rating scale. These scales provided interval-level data allowing the use of parametric statistics. The complexity and importance checks are shown in Figure 5 on page 38 and Figure 6 on page 39, respectively.

Experimental Apparatus

Hardware

Hardware used for the experiment consisted of an IBM InfoWindow Touch Screen Color Display, an IBM Personal System/2 Model 50 Z with full-size keyboard, and a Apartment Dimension Desirability scale. The touch screen display included a touch screen interface, voice synthesizer, videodisc player interface\(^9\), graphics overlay on video, and a personal computer interface control. The 13-inch monitor was a black matrix, tricolor, phosphor dot monitor capable of displaying both

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\(^8\) See "Appendix B. Algorithm for Calculating Decision Strategy Complexity Rating" on page 85 for a definition of an elimination period and a detailed description of this variable.

\(^9\) The videodisc player interface was not used, and is mentioned only to give a complete description of the hardware.
Figure 5. Complexity manipulation check.

How difficult was this problem?

1 2 3 4 5 6 7 8 9

very easy very difficult
Figure 6. Importance manipulation check.

How important was it to you to get the right answer?

1 2 3 4 5 6 7 8 9

not important  very important
NTSC\textsuperscript{10} composite video from a videodisc player and graphics from a personal computer. The touch screen was mounted on a rigid frame over the face of the CRT. The Apartment Dimension Desirability scale was a semantic differential, bipolar scale with 70 divisions and is shown in Figure 7 on page 41. It consisted of a 92-inch by 6-inch piece of cardboard covered with white paper and 70 attached paper clips. The scale ranged from -35 to +35 with every fifth number being printed (starting with -35).

Software

Three pieces of software were developed by the experimenter to setup and run the experiment and to convert experimental data into a format used by the SAS statistical analysis package on the Virginia Tech mainframe computer. The setup software was used to generate problem scenarios for a given subject based on information gathered from that subject. The software, which ran the experiment, presented the decision tasks to the subjects and collected time and touch screen input data. The conversion software organized data gathered during the experiment into a format used by SAS. All software was written and compiled using Microsoft QuickBASIC version 4.5 (Microsoft, 1987).

Decision Tasks

The decision tasks used in this study involved selecting an apartment to rent from a group of apartments. In generalizable terms, the task consisted of selecting one well-defined alternative from a bounded set of alternatives each varying along the same, well-defined dimensions. Each (fictitious)

\textsuperscript{10} National Television Standards Committee.
apartment was described along 7 dimensions or attributes. (Refer to Table 3 on page 35.) The group of apartments in any given trial was designed using information gathered from subjects during the pre-test phase of the study such that all apartments were about equally desirable and none were undesirable. The apartment descriptions were presented in a two-dimensional matrix displayed on the screen. The cells within this matrix contained values of specific dimensions for the apartments. A value was "hidden" by an asterisk until the subject requested it. The task ended when all apartments but one were eliminated.

**Procedure**

The experiment consisted of three phases. In Phase I, subjects were pretested for eligibility. In Phase II, information concerning apartment attribute preferences was collected from those subjects passing the screening procedures of the first phase. In Phase III, subjects were trained and presented with the experimental manipulations.

**Phase I**

In Phase I, subjects were pretested to determine if they were eligible to participate in the study. Demographic and physical requirements are outlined in the Subjects section. To be eligible, subjects must have scored as either high-impulsive or low-impulsive on the impulsivity test. Prior to taking the impulsivity test, subjects signed an informed consent form pertaining only to the screening portion of the study (i.e., Phase I). The consent form outlined the subject's right to withdraw from the study at any time and informed the subject that the experimenter was looking for certain ranges on a personality test and that failure to be selected for the study in no way reflected any defect or
deficiency in the subject. At the end of the screening, all subjects were be paid $2.00 and told that they would be contacted within one week if they were eligible.

Eligibility requirements were based on impulsivity scores and on gender. Therefore, since impulsivity and gender were two-level variables (i.e., high/low and male/female), there were four distinct groups of subjects.

Phase II

This phase consisted of collecting information from subjects concerning apartment attribute preferences and of two training sessions. Apartment attribute preference data were used to generate fictitious apartments used in Phase III of this study. Each subject selected for the study from Phase I was contacted and a meeting time was arranged. The subject first read an informed consent form (See “Appendix A. Participant's Informed Consent” on page 80.) containing both a general description of the experiment (which included any potential risks involved) and an outline of the subject’s rights including the right to withdraw from the study at any time. The subject indicated willingness to participate by signing and dating the informed consent form.

Data concerning apartment attribute preferences were then obtained. The subject was handed a randomly-ordered (i.e., shuffled) deck of 21 cards, each card measuring 1-inch by 3-inches. Each card contained one of three values from one of seven apartment dimensions. (See Table 3 on page 35 for a listing of all values and dimensions.) The subject was instructed to place the cards into three piles of seven cards each based on whether the subject perceived a value as desirable (pile 1), undesirable (pile 3), or in between these two extremes (pile 2). The subject was then instructed to rank order the cards within each pile from most desirable (or least undesirable) to least desirable (or most undesirable). Once the cards within each pile were rank-ordered, the subject placed the cards on the Apartment Dimension Desirability scale (See Figure 7 on page 41.) starting with pile 1 and
ending with pile 3. Once this was done, the subject and experimenter scheduled a time when the subject could return to participate in the main study. Payment was made after the subject completed Phase III of the study. Although subjects could withdraw from the study at any time without penalty, none withdrew.

The data collected using this method were used in the main experiment (Phase III) to determine which alternative apartment in a set of apartments the subject should have preferred. The method for collecting these preference data was based on multiple objective decision methods outlined by MacCrimmon (1973). Figure 8 on page 46 outlines the logic chart used to determine an appropriate method.

The first question in Figure 8 asked whether the purpose for collecting the data was normative or descriptive. In the present study, the purpose was to determine how the subject should choose; therefore, the purpose for collecting the data was normative. The next question asked whether a direct assessment of preferences was valid and reliable. MacCrimmon (1973) pointed out that, "in most situations, some valid, direct assessments of preferences can be gotten" (p. 38). Therefore the answer to this question was probably "yes." The next question asked whether there was more than one decision maker's preferences to be considered. Since subjects' preferences were considered individually, the answer was "no." The next question asked if only the best (or worst) attributes would be considered in the selection of an alternative. It could not be assumed that only the best or worst attributes would be considered by all subjects. Therefore, the answer to this question was "no." The next question asked whether the alternatives were to be designed or chosen from a list. In this experiment, alternatives were chosen from a list. The last question asked which was the most valid kind of preference data. In Figure 8 on page 46, the preference data is ordered from left to right based on how demanding the collection of the data is on the individual. The first method, collecting inter- and intra-attribute weights, would provide the most detail and most accurate preference information. Since there was no reason to assume that inter- and intra-attribute weights could not be obtained, three collection methods were available (A.2.b, A.2.c, and A.2.d in Figure 8 on page 46). The method selected was the simple additive weighting method (A.2.b)
which has been widely used (MacCrimmon, 1973) and is easier to implement than the other two available methods.

The first training session was criteria-based and was designed to familiarize the subject with the touch screen and its proper operation. On the touch screen display, the subjects were presented with a 10x7 matrix of asterisks identical to the one displayed in the high-complexity condition in the main experiment. One of the asterisks was blinking. The subject was instructed to touch the asterisk using his or her index finger, being as accurate as possible. After the touch was made—regardless of accuracy—the asterisk stopped blinking and another started to blink. The subject then touched this asterisk. This process continued until a total of forty-four touches were received. After the last touch, the computer displayed how many misinterpreted touches (i.e., errors) were made. If this number was greater than five (i.e., ten percent) training was repeated. Otherwise, the subject proceeded to the second training session.

In the second training session all subjects received the same amount of training (i.e., not criteria-based). This session was designed to familiarize the subject with the experimental task and the layout of information on the screen. Each screen was conceptually divided into five sections, shown in Figure 9 on page 47. Section 1 was the Acquisition Touch Area. Initially, this section was filled with asterisks. However, when one of these asterisks was touched, the dimension value “underneath” that asterisk was displayed until another touch was received. For example, if the asterisk in the first column and third row was touched, the rent value for apartment 1 was displayed (i.e., HIGH, AVG, or LOW). Dimension values (such as Rent, Noise Level, etc.) were displayed in section 2. In section 3, apartment numbers were displayed (i.e., 1,2,3,...etc.). Section 4 was the Elimination Touch Area. Touches made in this section signalled the elimination of an alternative. In section 5, the reward value for choosing the best apartment was displayed. The experimenter showed the subject each of these sections and explained its purpose or function.

Subjects performed two trials in each of three complexity conditions (i.e., two, five, or ten alternatives) presented randomly. At the beginning of each trial the subject read the reward value aloud.
Figure 8. Logic chart for the selection of a preference measure (copied from MacCrimmon, 1973).
Figure 9. The experimental display consists of five sections: (1) Acquisition Touch Area, (2) Dimension Names, (3) Apartment Numbers, (4) Elimination Touch Area, and (5) Reward Level.
to ensure he or she was aware of it. After reading the reward value aloud, the subject pressed the spacebar on the keyboard to begin. After each trial, the subject received the complexity and importance manipulation checks. (See Figure 5 on page 38 and Figure 6 on page 39.)

Phase III

Phase III was typically performed one or two days later than Phase II and consisted of one training session, a set of experimental manipulations (i.e., trials), and a debriefing. The training session was identical to the second training session performed during Phase II and served two purposes. First, it refreshed the subject's memory as to the operation of the touch screen and mentally prepared the subject for the actual data collection. Second, any extraneous behavior due to the novelty of interacting with a touch screen should have been removed or at least minimized. That is, any touches made to the touch screen should reflect a subject's desire to collect additional information—not to see how a touch screen works.

At the end of the last practice trial, the subject was allowed to rest for one minute and was asked if there were any questions. Any questions asked were answered and then the experimental trials began. The order in which different complexity and importance conditions were presented was counterbalanced using two identical sets of two orthogonal (i.e., non-overlapping) Latin Squares taken from Fisher (1974). (See Figure 10 on page 49.) The high-impulsive group and low-impulsive group received identical sets of Latin Squares. At the end of each trial, the touch screen display went blank and the subject received the importance manipulation check and complexity manipulation check, entering a rating for each via the computer keyboard.

After the rating was entered, the subject was allowed to rest for a period of time equal to 20% of the amount of time spent on the last trial. The computer, after making this calculation, displayed a "countdown" on the touch screen. When this countdown reached zero, the subject was asked to
Figure 10. Latin Squares used to counterbalance complexity and importance conditions (copied from Fisher, 1974).

KEY:

1.....medium complexity, medium importance
2.....low complexity, high importance
3.....high complexity, low importance
4.....medium complexity, high importance
5.....high complexity, high importance
6.....low complexity, low importance
7.....low complexity, medium importance
8.....high complexity, medium importance
9.....medium complexity, low importance

1 2 3 4 5 6 7 8 9
5 6 4 8 9 7 2 3 1
9 7 8 3 1 2 6 4 5
8 9 7 2 3 1 5 6 4
3 1 2 6 4 5 9 7 8
4 5 6 7 8 9 1 2 3
6 4 5 9 7 8 3 1 2
7 8 9 1 2 3 4 5 6
2 3 1 5 6 4 8 9 7

1 2 3 4 5 6 7 8 9
7 8 9 1 2 3 4 5 6
4 5 6 7 8 9 1 2 3
2 3 1 5 6 4 8 9 7
8 9 7 2 3 1 5 6 4
5 6 4 8 9 7 2 3 1
3 1 2 6 4 5 9 7 8
9 7 8 3 1 2 6 4 5
6 4 5 9 7 8 3 1 2
press a key to begin the next trial. After the subject completed the last trial, he or she received the performance-based monetary rewards (if any), was paid an additional $15.00 for participating ($10.00 for time spent plus an additional $5.00 bonus for completing the entire study), and was debriefed and dismissed. During the debriefing, the experimenter explained the experimental hypotheses to the subject, asked the subject if he or she wanted a copy of the results, and thanked the subject for participating.

Subjects

Thirty-six subjects (eighteen male and eighteen female) were used in this study. Two new subjects were added to the study to replace two subjects in the original group whose data were either lost or unusable. In one case, the subject’s data was inadvertently erased. In the other case, a post-experiment interview indicated the subject did not follow instructions. The same presentation order of the experimental conditions was used for the replacement subjects to maintain the Latin Square counterbalancing design. In addition to meeting the impulsivity requirements outlined earlier, subjects also met the following criteria:

- They were between eighteen and twenty-one years old.
- They lived in an undergraduate dormitory at Virginia Tech.
- They have not lived in an apartment within the past ten years.
- They had at least 20/40 minimum static visual acuity at short distances, corrected where necessary.
Results

All results were analyzed using four-way analysis of variance (ANOVA) procedures except for overall changes in decision strategy complexity ratings between successive elimination periods, tested using t tests.

**Manipulation Checks**

Two manipulation checks were used in this study, one for decision task complexity and one for decision importance. These were in the form of questions designed to measure the underlying constructs being manipulated. Table 4 on page 52 and Table 5 on page 53 show the analysis of variance (ANOVA) results for decision task complexity rating and decision importance rating, respectively.

As expected, only decision task complexity had a significant effect on the decision task complexity rating, $F(2,64) = 31.58$, $p = 0.0001$. Figure 11 on page 55 shows that as decision task complexity increased (i.e., the number of apartments increased), the problem complexity rating increased. A
Table 4. ANOVA Table for Decision Task Complexity Manipulation Check.

<table>
<thead>
<tr>
<th>SOURCE</th>
<th>df</th>
<th>SS</th>
<th>MS</th>
<th>F</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender (G)</td>
<td>1</td>
<td>0.03</td>
<td>0.03</td>
<td>0.00</td>
<td>.9698</td>
</tr>
<tr>
<td>Impulsivity (M)</td>
<td>1</td>
<td>21.26</td>
<td>21.26</td>
<td>1.12</td>
<td>.2988</td>
</tr>
<tr>
<td>G x M</td>
<td>1</td>
<td>4.23</td>
<td>4.23</td>
<td>0.22</td>
<td>.6410</td>
</tr>
<tr>
<td>Subjects (S/G,M)</td>
<td>32</td>
<td>609.93</td>
<td>19.06</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Complexity (C)</td>
<td>2</td>
<td>150.30</td>
<td>75.15</td>
<td>31.58</td>
<td>.0001</td>
</tr>
<tr>
<td>G x C</td>
<td>2</td>
<td>2.46</td>
<td>1.23</td>
<td>0.52</td>
<td>.5985</td>
</tr>
<tr>
<td>M x C</td>
<td>2</td>
<td>12.82</td>
<td>6.41</td>
<td>2.69</td>
<td>.0753</td>
</tr>
<tr>
<td>G x M x C</td>
<td>2</td>
<td>3.01</td>
<td>1.50</td>
<td>0.63</td>
<td>.5350</td>
</tr>
<tr>
<td>C x S/G,M</td>
<td>64</td>
<td>152.30</td>
<td>2.38</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Importance (I)</td>
<td>2</td>
<td>11.88</td>
<td>5.94</td>
<td>2.94</td>
<td>.0601</td>
</tr>
<tr>
<td>G x I</td>
<td>2</td>
<td>1.85</td>
<td>0.93</td>
<td>0.46</td>
<td>.6345</td>
</tr>
<tr>
<td>M x I</td>
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<td>1.51</td>
<td>0.75</td>
<td>0.37</td>
<td>.6904</td>
</tr>
<tr>
<td>G x M x I</td>
<td>2</td>
<td>4.32</td>
<td>2.16</td>
<td>1.07</td>
<td>.3494</td>
</tr>
<tr>
<td>I x S/G,M</td>
<td>64</td>
<td>129.33</td>
<td>2.02</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>C x I</td>
<td>4</td>
<td>4.79</td>
<td>1.20</td>
<td>0.88</td>
<td>.4761</td>
</tr>
<tr>
<td>G x C x I</td>
<td>4</td>
<td>4.96</td>
<td>1.24</td>
<td>0.92</td>
<td>.4574</td>
</tr>
<tr>
<td>M x C x I</td>
<td>4</td>
<td>4.83</td>
<td>1.21</td>
<td>0.89</td>
<td>.4720</td>
</tr>
<tr>
<td>G x M x C x I</td>
<td>4</td>
<td>7.64</td>
<td>1.91</td>
<td>1.41</td>
<td>.2347</td>
</tr>
<tr>
<td>C x I x S/G,M</td>
<td>128</td>
<td>173.56</td>
<td>1.36</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>323</td>
<td>1301.00</td>
<td>4.03</td>
<td>---</td>
<td>---</td>
</tr>
</tbody>
</table>
Table 5. ANOVA Table for Decision Importance Manipulation Check.

<table>
<thead>
<tr>
<th>SOURCE</th>
<th>df</th>
<th>SS</th>
<th>MS</th>
<th>F</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender (G)</td>
<td>1</td>
<td>15.12</td>
<td>15.12</td>
<td>1.45</td>
<td>.2378</td>
</tr>
<tr>
<td>Impulsivity (M)</td>
<td>1</td>
<td>8.35</td>
<td>8.35</td>
<td>0.80</td>
<td>.3782</td>
</tr>
<tr>
<td>G x M</td>
<td>1</td>
<td>0.05</td>
<td>0.05</td>
<td>0.00</td>
<td>.9456</td>
</tr>
<tr>
<td>Subjects (S/G,M)</td>
<td>32</td>
<td>334.40</td>
<td>10.45</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Complexity (C)</td>
<td>2</td>
<td>0.27</td>
<td>0.13</td>
<td>0.20</td>
<td>.8165</td>
</tr>
<tr>
<td>G x C</td>
<td>2</td>
<td>1.34</td>
<td>0.67</td>
<td>1.03</td>
<td>.3640</td>
</tr>
<tr>
<td>M x C</td>
<td>2</td>
<td>0.82</td>
<td>0.41</td>
<td>0.63</td>
<td>.5363</td>
</tr>
<tr>
<td>G x M x C</td>
<td>2</td>
<td>0.04</td>
<td>0.02</td>
<td>0.03</td>
<td>.9674</td>
</tr>
<tr>
<td>C x S/G,M</td>
<td>64</td>
<td>41.75</td>
<td>0.65</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Importance (I)</td>
<td>2</td>
<td>70.60</td>
<td>35.30</td>
<td>16.49</td>
<td>.0001</td>
</tr>
<tr>
<td>G x I</td>
<td>2</td>
<td>3.34</td>
<td>1.67</td>
<td>0.78</td>
<td>.4627</td>
</tr>
<tr>
<td>M x I</td>
<td>2</td>
<td>0.30</td>
<td>0.15</td>
<td>0.07</td>
<td>.9319</td>
</tr>
<tr>
<td>G x M x I</td>
<td>2</td>
<td>0.30</td>
<td>0.15</td>
<td>0.07</td>
<td>.9319</td>
</tr>
<tr>
<td>I x S/G,M</td>
<td>64</td>
<td>137.01</td>
<td>2.14</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>C x I</td>
<td>4</td>
<td>0.44</td>
<td>0.11</td>
<td>0.16</td>
<td>.9589</td>
</tr>
<tr>
<td>G x C x I</td>
<td>4</td>
<td>2.25</td>
<td>0.56</td>
<td>0.81</td>
<td>.5187</td>
</tr>
<tr>
<td>M x C x I</td>
<td>4</td>
<td>0.81</td>
<td>0.20</td>
<td>0.29</td>
<td>.8827</td>
</tr>
<tr>
<td>G x M x C x I</td>
<td>4</td>
<td>1.66</td>
<td>0.42</td>
<td>0.60</td>
<td>.6636</td>
</tr>
<tr>
<td>C x I x S/G,M</td>
<td>128</td>
<td>88.62</td>
<td>0.69</td>
<td>---</td>
<td>---</td>
</tr>
</tbody>
</table>

Total 323 707.47 2.19 --- ---

Results

53
Student-Newman-Keuls (SNK) test revealed that all differences between means were significant at \( \alpha = .05 \), resulting in three separate levels of decision task complexity.

Similar effects were found for the decision importance rating. Only decision importance had a significant effect, \( F(2,64) = 16.49, p = .0001 \). Figure 12 on page 56 shows that as decision importance increased (i.e., amount of reward increased), the decision importance rating increased. An SNK test revealed that all differences between means were significant, resulting in three separate levels of decision importance.

**Analysis for Decision Time**

Decision time was defined as the interval of time beginning when a set of alternatives (i.e., apartments) was initially displayed and ending when all alternatives but one have been eliminated. Table 6 on page 58 shows the ANOVA results for decision time, indicating significant effects from decision task complexity, \( F(2,64) = 163.34, p = .0001 \), and from the three-way interaction of gender, impulsivity, and decision task complexity, \( F(2,64) = 5.48, p = .0064 \). Figure 13 on page 59 displays decision times as a function of gender, impulsivity, and complexity. Two-way ANOVAs indicated that for females, there was a significant interaction between impulsivity and complexity, \( F(2,32) = 3.46, p = 0.0437 \). For high impulsives, there was a significant interaction between gender and complexity, \( F(2,32) = 7.03, p = 0.0029 \). One-way ANOVAs and SNK tests revealed that decision time increased as a function of decision task complexity for all combinations of gender and impulsivity. The absence of significant differences in decision time between males and females and between high and low impulsives indicates that these variables do not mediate the relationship between decision task complexity and decision time and can thus be ignored. Figure 14 on page 60 shows that as decision task complexity increased, decision time increased. An SNK test revealed that all differences between means were significant at \( \alpha = .05 \).
Figure 11. Complexity ratings increased as decision task complexity increased.
Figure 12. Importance ratings increased as decision importance increased.
Table 6. ANOVA Table for Decision Time.

<table>
<thead>
<tr>
<th>SOURCE</th>
<th>df</th>
<th>SS</th>
<th>MS</th>
<th>F</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender (G)</td>
<td>1</td>
<td>3741.36</td>
<td>3741.36</td>
<td>0.20</td>
<td>.6538</td>
</tr>
<tr>
<td>Impulsivity (M)</td>
<td>1</td>
<td>5852.25</td>
<td>5852.25</td>
<td>0.32</td>
<td>.5752</td>
</tr>
<tr>
<td>G x M</td>
<td>1</td>
<td>24527.04</td>
<td>24527.04</td>
<td>1.34</td>
<td>.2549</td>
</tr>
<tr>
<td>Subjects (S/G,M)</td>
<td>32</td>
<td>584058.54</td>
<td>18251.83</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Complexity (C)</td>
<td>2</td>
<td>2468403.91</td>
<td>1234201.95</td>
<td>163.34</td>
<td>.0001</td>
</tr>
<tr>
<td>G x C</td>
<td>2</td>
<td>9851.46</td>
<td>4925.73</td>
<td>0.65</td>
<td>.5245</td>
</tr>
<tr>
<td>M x C</td>
<td>2</td>
<td>4434.57</td>
<td>2217.29</td>
<td>0.29</td>
<td>.7467</td>
</tr>
<tr>
<td>G x M x C</td>
<td>2</td>
<td>82784.15</td>
<td>41392.08</td>
<td>5.48</td>
<td>.0064</td>
</tr>
<tr>
<td>C x S/G,M</td>
<td>64</td>
<td>483596.35</td>
<td>7556.19</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Importance (I)</td>
<td>2</td>
<td>23334.89</td>
<td>11667.45</td>
<td>1.65</td>
<td>.2008</td>
</tr>
<tr>
<td>G x I</td>
<td>2</td>
<td>5588.07</td>
<td>2794.04</td>
<td>0.39</td>
<td>.6758</td>
</tr>
<tr>
<td>M x I</td>
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<td>23851.19</td>
<td>11925.60</td>
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</tr>
<tr>
<td>G x M x I</td>
<td>2</td>
<td>11540.47</td>
<td>5770.24</td>
<td>0.81</td>
<td>.4475</td>
</tr>
<tr>
<td>I x S/G,M</td>
<td>64</td>
<td>453537.83</td>
<td>7086.53</td>
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<td></td>
</tr>
<tr>
<td>C x I</td>
<td>4</td>
<td>31893.70</td>
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<td>.3400</td>
</tr>
<tr>
<td>G x C x I</td>
<td>4</td>
<td>597.52</td>
<td>149.38</td>
<td>0.02</td>
<td>.9991</td>
</tr>
<tr>
<td>M x C x I</td>
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<td>16887.30</td>
<td>4221.82</td>
<td>0.60</td>
<td>.6601</td>
</tr>
<tr>
<td>G x M x C x I</td>
<td>4</td>
<td>10285.31</td>
<td>2571.33</td>
<td>0.37</td>
<td>.8310</td>
</tr>
<tr>
<td>C x I x S/G,M</td>
<td>128</td>
<td>894013.06</td>
<td>6984.48</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>323</td>
<td>5138778.97</td>
<td>15909.53</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure 13. Effects of complexity, impulsivity, and gender on decision time.
Figure 14. Effect of decision task complexity on decision time.
Analysis for Amount of Information Searched

The amount of information searched was defined as the total number of cells "uncovered" in the Acquisition Touch Area (See Figure 9 on page 47.) during the course of a trial. Table 7 on page 61 shows the ANOVA results for amount of information searched. Only decision task complexity had a significant effect on the amount of information searched, $F(2,64) = 117.14, p = .0001$. Figure 15 on page 62 shows that as decision task complexity increased, the amount of information searched increased. An SNK test revealed that all differences between means were significant at $\alpha = .05$.

The analysis for the average amount of information searched per alternative (AVGI) is shown in Table 8 on page 63. This measure was calculated by dividing the amount of information searched during the course of a trial by the number of alternatives appearing at the beginning of that trial (i.e., 2, 5, or 10 aps). The ANOVA results indicated significant main effects were obtained from decision task complexity and significant three-way interaction effects were obtained from gender, impulsivity, and decision task complexity, and gender, impulsivity, and decision importance. Although there was a significant four-way interaction between gender, impulsivity, decision task complexity, and decision importance, such interactions are often difficult if not impossible to explain. Since a number of ANOVAs were run and the effect had only borderline significance, $F(4,128) = 2.48, p = .0471$, it is likely that this result was spurious.

Two-way ANOVAs indicated a significant interaction between impulsivity and decision task complexity for males, $F(2,32) = 4.73, p = 0.0159$, and a significant interaction between impulsivity and decision importance for males, $F(2,32) = 3.41, p = 0.0456$. One-way ANOVAs and SNK tests revealed that the mean AVGI for low impulsive males was significantly greater in the five apartment decision task complexity condition than in the two-apartment condition at $\alpha = .05$. No other significant differences in means were found. Figure 16 on page 65 shows the relationship between...
Table 7. ANOVA Table for Amount of Information Searched

<table>
<thead>
<tr>
<th>SOURCE</th>
<th>df</th>
<th>SS</th>
<th>MS</th>
<th>F</th>
<th>( \mu )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender (G)</td>
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<td>831.36</td>
<td>831.36</td>
<td>0.08</td>
<td>.7819</td>
</tr>
<tr>
<td>Impulsivity (M)</td>
<td>1</td>
<td>10033.36</td>
<td>10033.36</td>
<td>0.94</td>
<td>.3394</td>
</tr>
<tr>
<td>G x M</td>
<td>1</td>
<td>780.89</td>
<td>780.89</td>
<td>0.07</td>
<td>.7884</td>
</tr>
<tr>
<td>Subjects (S/G,M)</td>
<td>32</td>
<td>341292.79</td>
<td>10665.40</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Complexity (C)</td>
<td>2</td>
<td>575350.38</td>
<td>287675.19</td>
<td>117.14</td>
<td>.0001</td>
</tr>
<tr>
<td>G x C</td>
<td>2</td>
<td>1180.57</td>
<td>590.29</td>
<td>0.24</td>
<td>.7871</td>
</tr>
<tr>
<td>M x C</td>
<td>2</td>
<td>12231.35</td>
<td>6115.68</td>
<td>2.49</td>
<td>.0909</td>
</tr>
<tr>
<td>G x M x C</td>
<td>2</td>
<td>1841.67</td>
<td>920.84</td>
<td>0.37</td>
<td>.6888</td>
</tr>
<tr>
<td>C x S/G,M</td>
<td>64</td>
<td>157174.25</td>
<td>2455.85</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Importance (I)</td>
<td>2</td>
<td>1059.75</td>
<td>529.87</td>
<td>0.74</td>
<td>.4809</td>
</tr>
<tr>
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<tr>
<td>M x I</td>
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<td>332.06</td>
<td>166.03</td>
<td>0.23</td>
<td>.7936</td>
</tr>
<tr>
<td>G x M x I</td>
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<td>3950.64</td>
<td>1975.32</td>
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<td>.0708</td>
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<tr>
<td>I x S/G,M</td>
<td>64</td>
<td>45789.43</td>
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<td>---</td>
<td>---</td>
</tr>
<tr>
<td>C x I</td>
<td>4</td>
<td>960.42</td>
<td>240.10</td>
<td>0.49</td>
<td>.7453</td>
</tr>
<tr>
<td>G x C x I</td>
<td>4</td>
<td>2026.74</td>
<td>506.69</td>
<td>1.03</td>
<td>.3957</td>
</tr>
<tr>
<td>M x C x I</td>
<td>4</td>
<td>1204.15</td>
<td>301.04</td>
<td>0.61</td>
<td>.6558</td>
</tr>
<tr>
<td>G x M x C x I</td>
<td>4</td>
<td>2877.83</td>
<td>719.46</td>
<td>1.46</td>
<td>.2185</td>
</tr>
<tr>
<td>C x I x S/G,M</td>
<td>128</td>
<td>631177.51</td>
<td>493.10</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>323</td>
<td>1223023.96</td>
<td>3786.45</td>
<td>---</td>
<td>---</td>
</tr>
</tbody>
</table>
Figure 15. Effect of decision task complexity on amount of information searched.
Table 8. ANOVA Table for Average Amount of Information Searched per Apartment.

<table>
<thead>
<tr>
<th>SOURCE</th>
<th>df</th>
<th>SS</th>
<th>MS</th>
<th>F</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender (G)</td>
<td>1</td>
<td>16.76</td>
<td>16.76</td>
<td>0.05</td>
<td>.8172</td>
</tr>
<tr>
<td>Impulsivity (M)</td>
<td>1</td>
<td>148.43</td>
<td>148.43</td>
<td>0.48</td>
<td>.4931</td>
</tr>
<tr>
<td>G x M</td>
<td>1</td>
<td>3.85</td>
<td>3.85</td>
<td>0.01</td>
<td>.9118</td>
</tr>
<tr>
<td>Subjects (S/G,M)</td>
<td>32</td>
<td>9880.99</td>
<td>308.78</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Complexity (C)</td>
<td>2</td>
<td>201.54</td>
<td>100.77</td>
<td>4.57</td>
<td>.0139</td>
</tr>
<tr>
<td>G x C</td>
<td>2</td>
<td>9.84</td>
<td>4.92</td>
<td>0.22</td>
<td>.8006</td>
</tr>
<tr>
<td>M x C</td>
<td>2</td>
<td>92.46</td>
<td>46.23</td>
<td>2.10</td>
<td>.1311</td>
</tr>
<tr>
<td>G x M x C</td>
<td>2</td>
<td>138.87</td>
<td>69.43</td>
<td>3.15</td>
<td>.0495</td>
</tr>
<tr>
<td>C x S/G,M</td>
<td>64</td>
<td>1410.57</td>
<td>22.04</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Importance (I)</td>
<td>2</td>
<td>28.20</td>
<td>14.10</td>
<td>0.78</td>
<td>.4646</td>
</tr>
<tr>
<td>G x I</td>
<td>2</td>
<td>4.84</td>
<td>2.42</td>
<td>0.13</td>
<td>.8755</td>
</tr>
<tr>
<td>M x I</td>
<td>2</td>
<td>21.14</td>
<td>10.57</td>
<td>0.58</td>
<td>.5620</td>
</tr>
<tr>
<td>G x M x I</td>
<td>2</td>
<td>115.04</td>
<td>57.52</td>
<td>3.16</td>
<td>.0489</td>
</tr>
<tr>
<td>I x S/G,M</td>
<td>64</td>
<td>1163.36</td>
<td>18.18</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>C x I</td>
<td>4</td>
<td>31.89</td>
<td>7.97</td>
<td>0.51</td>
<td>.7294</td>
</tr>
<tr>
<td>G x C x I</td>
<td>4</td>
<td>128.56</td>
<td>32.14</td>
<td>2.05</td>
<td>.0911</td>
</tr>
<tr>
<td>M x C x I</td>
<td>4</td>
<td>55.93</td>
<td>13.98</td>
<td>0.89</td>
<td>.4707</td>
</tr>
<tr>
<td>G x M x C x I</td>
<td>4</td>
<td>155.49</td>
<td>38.87</td>
<td>2.48</td>
<td>.0471</td>
</tr>
<tr>
<td>C x I x S/G,M</td>
<td>128</td>
<td>2005.89</td>
<td>15.67</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Total</td>
<td>323</td>
<td>15613.66</td>
<td>48.34</td>
<td>---</td>
<td>---</td>
</tr>
</tbody>
</table>

Results
decision task complexity and AVGI. The results of an SNK test revealed that only the means for the two-apartment and five-apartment levels of decision task complexity differed significantly at $\alpha = .05$.

**Analysis for Average Decision Strategy Complexity Rating**

The decision strategy complexity rating for a given elimination period was defined as the number of unique dimensions divided by the number of unique apartments examined during that period. The average decision strategy complexity rating was defined as the sum, across elimination periods, of the complexity ratings for a given trial. Table 9 on page 66 shows the ANOVA results, indicating significant main effects for impulsivity, $F(1,32) = 4.45, p = .0428$, and decision task complexity, $F(2,64) = 114.75, p = .0001$. A significant two-way interaction was also found for these variables, $F(2,64) = 7.17, p = .0016$.

Figure 17 on page 67 shows the relationship between average decision strategy complexity rating and level of complexity for high- and low-impulsivity. One-way ANOVAs and SNK tests indicated that all differences between means for the high-impulsivity group were significant at $\alpha = .05$. For the low-impulsivity group, only the difference in means for the two-apartment and ten-apartment decision task complexity conditions were significant at $\alpha = .05$. Furthermore, SNK tests revealed significant differences in the means for the five-apartment and ten-apartment decision task complexity conditions.

SNK tests were also run to determine the nature of the main effects of impulsivity and decision task complexity. Figure 18 on page 69 shows that increases in decision task complexity led to decreases in average decision strategy complexity rating. Figure 19 on page 70 shows that high-impulsive
Figure 16. Effect of complexity on AVGI.
Table 9. ANOVA Table for Decision Strategy Complexity Rating.

<table>
<thead>
<tr>
<th>SOURCE</th>
<th>df</th>
<th>SS</th>
<th>MS</th>
<th>F</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender (G)</td>
<td>1</td>
<td>1.42</td>
<td>1.42</td>
<td>0.12</td>
<td>.7289</td>
</tr>
<tr>
<td>Impulsivity (M)</td>
<td>1</td>
<td>51.75</td>
<td>51.75</td>
<td>4.45</td>
<td>.0428</td>
</tr>
<tr>
<td>G x M</td>
<td>1</td>
<td>0.51</td>
<td>0.51</td>
<td>0.04</td>
<td>.8351</td>
</tr>
<tr>
<td>Subjects (S/G,M)</td>
<td>32</td>
<td>372.03</td>
<td>11.63</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Complexity (C)</td>
<td>2</td>
<td>238.70</td>
<td>119.35</td>
<td>114.75</td>
<td>.0001</td>
</tr>
<tr>
<td>G x C</td>
<td>2</td>
<td>0.48</td>
<td>0.24</td>
<td>0.23</td>
<td>.7936</td>
</tr>
<tr>
<td>M x C</td>
<td>2</td>
<td>14.91</td>
<td>7.46</td>
<td>7.17</td>
<td>.0016</td>
</tr>
<tr>
<td>G x M x C</td>
<td>2</td>
<td>0.53</td>
<td>0.26</td>
<td>0.25</td>
<td>.7762</td>
</tr>
<tr>
<td>C x S/G,M</td>
<td>64</td>
<td>66.56</td>
<td>33.28</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Importance (I)</td>
<td>2</td>
<td>0.99</td>
<td>0.49</td>
<td>0.85</td>
<td>.4330</td>
</tr>
<tr>
<td>G x I</td>
<td>2</td>
<td>0.30</td>
<td>0.15</td>
<td>0.26</td>
<td>.7734</td>
</tr>
<tr>
<td>M x I</td>
<td>2</td>
<td>0.08</td>
<td>0.04</td>
<td>0.07</td>
<td>.9330</td>
</tr>
<tr>
<td>G x M x I</td>
<td>2</td>
<td>1.38</td>
<td>0.69</td>
<td>1.19</td>
<td>.3119</td>
</tr>
<tr>
<td>I x S/G,M</td>
<td>64</td>
<td>37.35</td>
<td>0.58</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>C x I</td>
<td>4</td>
<td>0.11</td>
<td>0.03</td>
<td>0.07</td>
<td>.9917</td>
</tr>
<tr>
<td>G x C x I</td>
<td>4</td>
<td>2.58</td>
<td>0.65</td>
<td>1.60</td>
<td>.1770</td>
</tr>
<tr>
<td>M x C x I</td>
<td>4</td>
<td>0.81</td>
<td>0.20</td>
<td>0.50</td>
<td>.7352</td>
</tr>
<tr>
<td>G x M x C x I</td>
<td>4</td>
<td>2.83</td>
<td>0.71</td>
<td>1.76</td>
<td>.1405</td>
</tr>
<tr>
<td>C x I x S/G,M</td>
<td>128</td>
<td>51.46</td>
<td>0.40</td>
<td>--</td>
<td>--</td>
</tr>
</tbody>
</table>

Total 323 844.80 2.62 -- --
Figure 17. Effects of complexity and impulsivity on decision strategy complexity rating.

![Bar chart showing the effects of complexity and impulsivity on decision strategy complexity rating.](chart.png)
subjects used less complex decision strategies than low-impulsive subjects. SNK tests revealed that all differences between means were significant at $\alpha = .05$.

**Analysis for Changes in Decision Strategy Complexity**

Decision strategy complexity ratings were calculated for all elimination periods in the five- and ten-apartment decision task complexity conditions as described in "Appendix B. Algorithm for Calculating Decision Strategy Complexity Rating" on page 85. The number of increases and decreases in decision task complexity between successive elimination periods was calculated and the results are shown in Figure 20 on page 71. The means and $t$ test results are presented in Table 10 on page 72. The results indicate that there were significantly more increases than decreases in decision strategy complexity between successive elimination periods.
Figure 18. Effect of decision task complexity on decision strategy complexity rating.
Figure 19. Effect of impulsivity on decision strategy complexity rating.
Figure 20. Changes in decision strategy complexity rating as a function of complexity.
Table 10. Means and t Test Results for Decision Strategy Complexity Rating.

<table>
<thead>
<tr>
<th>Change in Complexity Rating</th>
<th>Mean</th>
<th>Standard Error</th>
<th>t</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Increase (5 Apt)</td>
<td>5.17</td>
<td>0.2236</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Decrease (5 Apt)</td>
<td>2.81</td>
<td>0.2024</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Difference (5 Apt)</td>
<td>2.36</td>
<td>0.3825</td>
<td>6.17</td>
<td>0.0001</td>
</tr>
<tr>
<td>Increase (10 Apt)</td>
<td>11.89</td>
<td>0.3131</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Decrease (10 Apt)</td>
<td>8.67</td>
<td>0.3212</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Difference (10 Apt)</td>
<td>3.22</td>
<td>0.5181</td>
<td>6.22</td>
<td>0.0001</td>
</tr>
</tbody>
</table>
Discussion

Summary

Overall, subjects spent more time, searched more information, and used less-complex decision strategies for more-complex decision tasks. Decision importance did not have any significant effects on the dependent variables used to test the hypotheses. This was due possibly to the limited range of this manipulation. Impulsivity effects were found primarily in the complexity of decision strategies with high-impulsive subjects using less-complex decision strategies than low-impulsive subjects. Other than an occasional interaction with impulsivity and complexity, gender did not produce any significant differences in the various measures of decision making behavior.
Manipulation Checks

The results indicated that decision task complexity and decision importance were successfully manipulated. Three statistically significant levels of each were obtained. However, the narrow range in means for both decision task complexity and decision importance (5.14 - 6.81 and 6.26 - 7.40, respectively) indicated that neither manipulation was entirely successful. Therefore, all results involving these variables should be interpreted accordingly. The narrow range in means for the decision task complexity rating indicates that factors other than just the number of apartments were affecting the ratings. Post-experiment interviews with subjects indicated that their ratings may have been influenced by the difficulty involved in choosing between very similar apartments.

Post-experiment interviews were also conducted to determine why the decision importance manipulation resulted in only minor changes in decision importance ratings. Most subjects indicated that, regardless of reward level (the manipulation for decision importance), they were motivated to find the “right” answer. Furthermore, subjects may have been trying to maximize the overall reward rather than focusing on rewards for individual trials. For future experiments of this kind, it is recommended that severe time limitations be placed on subjects, thus forcing them to attend to individual rewards rather than overall rewards.

Hypotheses

Figure 14 on page 60 provides support for hypothesis H1 which stated that an increase in decision task complexity would lead to an increase in decision time. Figure 13 on page 59 shows that this hypothesis holds true for all combinations of gender and impulsivity. Figure 16 on page 65 shows an increase in the average amount of information searched per apartment (AVGI) between the
two-apartment and five-apartment decision task complexity conditions followed by a decrease between the five-apartment and ten-apartment decision task complexity conditions. These results fail to support hypothesis \( H_2 \), which stated that an increase in decision task complexity would lead to a decrease in AVGI. This lack of support for hypothesis \( H_2 \) is somewhat surprising given the literature support provided by Payne (1976), Lussier and Olshavsky (1979), and Olshavsky (1979). However, the relatively high decision importance ratings (See Figure 12 on page 56.) and the absence of any time limits may have washed out this effect. Furthermore, although subjects in this study did not search less information per alternative as decision task complexity increased, Figure 18 on page 69 indicates that they did use less-complex strategies as decision task complexity increased.

Hypothesis \( H_3 \) stated that, for high-complexity decision tasks (i.e., decision tasks with five or ten apartments), subjects would initially use less-complex, noncompensatory decision strategies and then switch to more-complex, compensatory decision strategies. Furthermore, \( H_4 \) stated that this switch would occur as a function of the number of remaining apartments at any point in a given trial. The decision strategy complexity rating, described in “Appendix B. Algorithm for Calculating Decision Strategy Complexity Rating” on page 85, was devised to test this hypothesis. Figure 20 on page 71 shows strong support for this hypothesis for both the five- and ten-apartment decision task complexity conditions. This finding is particularly important for two reasons. First, it suggests that decision strategy selection is a dynamic rather than static process, contingent upon changes in the problem as it is being solved. Second, it provides at least face validity to the objective measure of decision strategy complexity outlined in “Appendix B. Algorithm for Calculating Decision Strategy Complexity Rating” on page 85. This measure should prove useful for further studies of this type.

\( H_5 \) and \( H_6 \) stated, respectively, that an increase in decision importance would lead to an increase in decision time and an increase in the amount of information searched before making a decision. Neither hypothesis was supported. This is not surprising since, although statistically significant, the means for the three levels of decision importance only covered a narrow range (6.26 - 7.40). As
suggested earlier, placing severe time limits on the subjects while maintaining the reward structure used to manipulate decision importance should result in a greater range in decision importance ratings.

H7 and H8 stated, respectively, that high-impulsive subjects would decide more quickly and search less information than low-impulsive subjects. No significant differences were found for either measure. However, on average, high-impulsive subjects did use significantly less-complex decision strategies than low impulsive subjects as indicated in Figure 19 on page 70. The differences in complexity ratings without corresponding differences in decision time or amount of information searched indicates that high-impulsive subjects were perhaps less efficient in executing their decision strategies.
Conclusions

The problem statement guiding this research was, "What effect do decision task complexity, decision importance, and decision maker impulsivity have on the selection of decision strategies for problems involving the selection of one alternative from a bounded set of known alternatives?" The results of this study clearly indicate that, for the population of subjects represented by this sample, decision making behavior is highly contingent upon problem complexity. The decrease in decision strategy complexity ratings as a function of decision task complexity indicates that individuals consider costs, in terms of effort, when selecting decision strategies. This lends support to both the theoretical decision strategy selection mechanism proposed by Christensen-Szalanski (1978) and the modified decision strategy mechanism presented here.

Unfortunately, little can be said about decision importance since there is a question of the degree to which this variable was manipulated, due to the limited range. However, evidence in the literature (Christensen-Szalanski, 1978; McAllister, Mitchell, and Beach, 1979; Billings and Scherer, 1988; Smith, Mitchell, and Beach, 1982) suggests that further study of decision importance is warranted.

Impulsivity was included as a variable in this study without much empirical support. For this reason, subjects at the extremes of impulsivity were chosen to determine if future studies of the re-
relationship between impulsivity and decision strategy selection is warranted. Since IQ was not controlled in this study, if a relationship between impulsivity and intelligence exists, differences in intelligence could account for differences attributed to impulsivity. However, studies by Hauenstein (1990) failed to show any correlation between IQ and impulsivity. The results indicate that further study is warranted to determine how impulsivity manifests itself in the selection of decision strategies.

Finally, perhaps the most significant contributions of this research to the study of decision making behavior were the tools and methods developed to manipulate the variables and collect the data, and the objective measure of decision strategy complexity. By using the computer together with a touch screen interface, great amounts of rich data were able to be accurately recorded and analyzed. Breaking the information search data down into "elimination periods" provided a dynamic, objective look at the decision making process and should be utilized in future studies, complimenting existing process-oriented analysis techniques such as verbal protocols. The objective measure of decision strategy complexity outlined in "Appendix B. Algorithm for Calculating Decision Strategy Complexity Rating" on page 85 should also prove useful in future studies of the kind presented here. The decision strategy complexity rating, when tracked over the course of a problem, should provide useful insights into contingent decision strategy selection.

**Recommendations for Further Research**

There was general support for both the theoretical decision strategy selection mechanism presented in this thesis and for the decision strategy selection mechanism on which it is based (Christensen-Szalanski, 1978). However, this study was not designed to critically compare the two theories. An experiment is needed which will create conditions such that the two theories will contradict each other. In addition, these theories both rely on cost/benefit relationships in the selection of decision
strategies. Better methods for characterizing the costs of different decision strategies and their associated benefits need to be developed. The decision strategy complexity rating developed in this thesis was a step in that direction. Finally, this study only examined a few decision maker, decision task, and decision characteristics. The results indicated that decision strategy selection was highly contingent on these characteristics, particularly decision task characteristics. Further studies are needed to identify variables upon which decision strategy selection is contingent.
Appendix A. Participant’s Informed Consent

Screening Test for Decision Making Study

Introduction

The purpose of this test is to find students to participate in a decision making study who have certain personality characteristics. The decision making study is being conducted by Management Systems Laboratories, a research arm of the Department of Industrial Engineering and Operations Research, Virginia Polytechnic and State University, Blacksburg, Virginia 24060 (telephone number: (703) 231-3501). The research team consists of Tom Polk, a graduate student in Industrial Engineering and Operations Research, under the direction of Dr. Harold A Kurstedt and Dr. Walter W. Wierwille who are the principal investigators.

The personality test you will take consists of 40 True-False statements designed to measure various aspects of your personality. There are no right or wrong answers. The results of this test will be used to select students to participate in the decision making study. Not being accepted into the
main study in no way indicates a deficiency in your personality. The experimenter is simply looking for certain personality characteristics, so it is important that you answer as accurately as possible.

After reading the introductory material, you will be given an informed consent form. If you understand what this test entails and agree to take it, you must sign this form.

**Procedure**

On the first page following the informed consent form you will find a general information form. Please answer all the questions. The screening test begins on the next page. You will be presented with 40 True-False statements. Please read each statement carefully and circle the letter “T” if it describes you or “F” if it does not. In those cases where you feel neither a “T” nor an “F” accurately describes you, please circle the one that describes you the best. That is, please circle either “T” or “F” for all 40 questions.

Once you have completed the test, please bring the entire packet to the front of the room where the experimenter will verify that you have answered all 40 questions and that you have provided all necessary information. You will then receive $2.00 for taking the test. In order to receive the money, you must write your name and social security number on the last form in your packet. This is for accounting purposes only and is a University requirement.

**Additional Information**

At any time during the test, if you no longer wish to continue, you have the right to terminate your participation; you will be compensated proportionately for your participation up to that point.
If you have any questions about the test or your rights as a participant after reading the attached consent form, please do not hesitate to ask. We will answer your questions honestly and as openly as possible. We ask that you do not discuss details of this test with any person, particularly those who may participate, as prior knowledge of seemingly incidental facts might compromise the data. It is expected that all data will be collected by May 1, 1990; you may feel free to discuss the study with any persons after that time.

Decision Making Study

Introduction

The purpose of this study is to evaluate decision making concerning the selection of an apartment. The study is being conducted by Management Systems Laboratories, a research arm of the Department of Industrial Engineering and Operations Research, Virginia Polytechnic Institute and State University, Blacksburg, Virginia 24060 (telephone number: (703) 231-3501). The research team consists of Tom Polk, a graduate student in Industrial Engineering and Operations Research, under the direction of Dr. Harold A. Kurstedt, the principal investigator.

This study involves two phases which will occur on two separate occasions, one today and one which will be scheduled at your convenience. In the first phase of this study, you will be asked to rate various dimensions of apartments such as rent and noise level in terms of their desirability. In the second phase of the study, you will be asked to select the best apartment from a set of apartments which vary along the dimensions provided in the first phase. This will involve interacting with a computer and a touch screen display which recognizes the coordinates of touches made to the screen's surface.
After reading the introductory material, you will be given an informed consent form. If you understand what this experiment entails and agree to participate in it, you must sign this form.

**Experimental Procedure: Phase I**

You will be handed a deck of twenty-one cards measuring three inches by one inch. Each of these cards will contain a statement such as “The rent is high”. Each of these statements will correspond to one of seven apartment dimensions such as rent, noise level, etc. You will be asked to rate each statement according to its desirability to you. After you have rated the dimensions, you will be trained on how to use a touch screen, a CRT display capable of recognizing the coordinates of touches made to the display’s surface. You will also be trained how to perform the experimental task.

**Experimental Procedure: Phase II**

You will be presented with nine sessions involving the selection of one apartment from a set of either two, five, or ten apartments. Although none of the apartments in a given session will be far superior to the rest, one will be best according to the desirability ratings you provided in the previous phase of this study.

Your task in each session is to choose the best apartment from the set of apartments displayed in each session. You will eliminate apartments one-by-one until only one remains. This apartment is your selection. Once an apartment has been eliminated, it will disappear from the screen and cannot be re-evaluated. You may use as much or as little of the information available and may take as much or as little time as you like before making a decision. At the end of each session you will rate how important it was to you to get the right answer and how difficult the problem was. If you
pick the apartment that--according to your own desirability ratings--is the best, you will earn a reward of either $0.25, $0.75, or $2.00. The amount of the reward will be displayed throughout each session. You will not know how much money you earned until the end of the last session.

Let me emphasize again, the amount of time or effort you spend in any given session is entirely up to you.

Additional Information

At any time during the study, if you no longer wish to continue, you have the right to terminate your participation; you will be compensated for your participation up to that point.

If you have any questions about the study or your rights as a participant after reading the attached consent form, please do not hesitate to ask. We will answer your questions honestly and as openly as possible. We ask that you do not discuss the details of this study with any person, particularly those who may participate, as prior knowledge of seemingly incidental facts might compromise the data. It is expected that all data will be collected by May 1, 1990; you may feel free to discuss the study with any persons after that time. All data will be analyzed with anonymity. Immediately upon completion of your experimental sessions, your data will be identified only by a randomly assigned serial number.
Appendix B. Algorithm for Calculating Decision Strategy Complexity Rating

The decision strategy complexity rating is a measure used to index the overall complexity of decision strategies based on the number of dimensions per alternative a given strategy considers. The measure is based on one simple assumption: the more information a decision strategy takes into account when evaluating a given alternative, the more complex that strategy is. A strategy which considers only rent, for example, when evaluating the desirability of an apartment is less complex than one which considers rent, noise level, and cleanliness. The logic behind this assumption is that every time a new dimension is examined for a particular alternative, this new information must be integrated with information previously obtained about that alternative to arrive at an overall evaluation.

The decision strategy complexity rating is calculated for each "elimination period." Elimination periods break up data collected during the decision making process into meaningful units and are used to detect changes in decision strategies employed during the decision making process by examining the content of information contained in each period. An elimination period is defined as the period between successive eliminations of alternatives in which new information is acquired. For any given problem, if there are $n$ alternatives, there will be a maximum of $n-1$ elimination pe-
riods. However, if no new information is acquired during an elimination period, the resulting elimination of an alternative is considered part of the previous elimination period. Therefore, each elimination period will contain at least one piece of information not acquired in the previous elimination period. Decision strategy complexity rating for a given elimination period is calculated by counting the number of dimensions within each alternative that were examined at least once. If at least one dimension has been examined for a given alternative, that alternative is considered to be “active,” otherwise it is considered to be “inactive.” The number of dimensions examined are then summed across all active alternatives and divided by the number of active alternatives. This number is the decision strategy complexity rating.

This rating has two unique characteristics. First, it does not matter how many times the same dimension for a given alternative is examined; it is a binary measurement with each dimension for each alternative having a value of either “examined” or “not examined.” This will separate the overall complexity of a decision strategy from the amount of effort an individual spent applying that decision strategy. Second, the rating is insensitive to the number of alternatives to which the strategy is applied. Again, this separates the complexity of a strategy from the effort used to apply it and thereby allows comparisons in decision strategy complexity for problems involving different numbers of alternatives.
Appendix C. References


Appendix C. References


Vita

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