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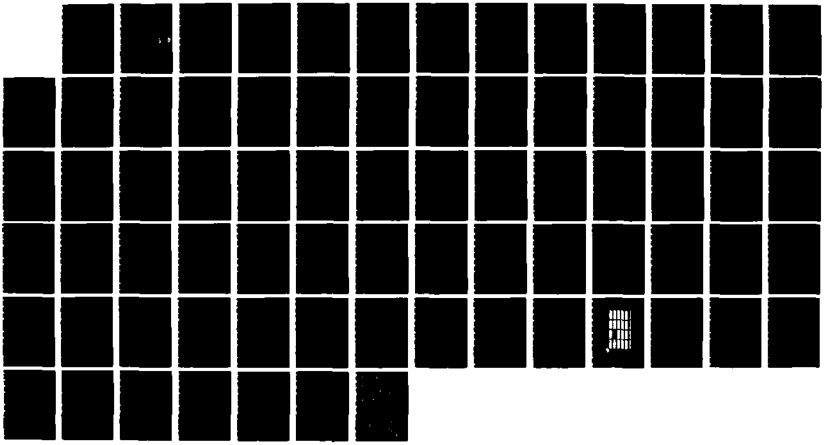

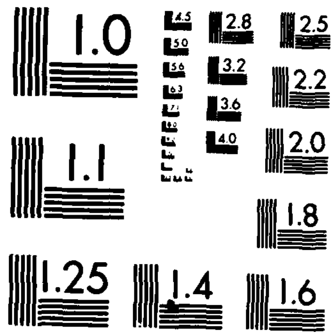

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ADAPTIVE STRATEGY SELECTION IN DECISION MAKING

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We examine the role of effort and accuracy in the adaptive use of decision processes. A computer simulation study that used the concept of elementary information processes identified heuristic choice strategies which approximate the accuracy of normative procedures while requiring substantially less effort. However, no single heuristic did well across all task and context conditions. Of particular interest was the finding that under time constraints, several heuristics were clearly more accurate than a normative procedure. Two process tracing studies showed a significant degree of correspondence between the

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SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered) efficient strategies for a given decision problem identified by the simulation and actual decision behavior. People were highly adaptive to changes in the nature of the alternatives available to them and to the presence of time pressure.

Much research has been devoted to describing the information processing strategies people use for making choices (Bettman, 1979; Svenson, 1979). Initially, this research focused on strategies that implied a complete search of all relevant information about the alternatives and that also allowed the good and bad aspects of each alternative to compensate for one another. Examples of such decision rules are the various expectation models of risky choice and the additive utility model of multiattribute choice. Simon (1955), however, suggested that decision strategies like additive utility were incompatible with our knowledge of human cognition. Furthermore, such models failed to account for important empirical findings, such as intransitivity in preferences (Tversky, 1969). Consequently, a number of simplified decision rules, or choice heuristics, have been proposed. Such heuristics reduce information processing demands by ignoring some potentially relevant problem information and by avoiding tradeoffs among values. For example, the lexicographic heuristic (Tversky, 1969) chooses the alternative which is best on the most important attribute, ignoring all other information. While heuristics can reduce information processing demands, they can also lead to decision errors such as intransitivities.

One of the major empirical findings of recent decision research is that an individual will use a variety of strategies for making a choice. Sometimes a person will use a compensatory type of strategy. At other times, the same person will use a noncompensatory decision strategy. The use of a particular strategy appears to be contingent on a number of task and context variables (Payne, 1982). Task variables are general characteristics of the decision problem, such as number of alternatives and time pressure, which are not dependent on the particular values of the alternatives in the decision set. Context variables, in contrast, are associated with the particular values of the choice objects, such as the correlation between attributes. One example of a contingency effect is the increase in the use of simplifying heuristics as the number of alternatives increases (Payne, 1976).

Evidence of contingent information processing in decisions has raised the question of why certain decision strategies are applied to solve certain decision problems. In other words, what determines the decision on how to choose? One general perspective in trying to answer that question looks at strategy selection as a function of both its costs, primarily the effort required to use a rule, and its benefits, primarily the ability of a strategy to select the best alternative (Beach & Mitchell, 1978; Russo & Dosher, 1983). The advantage of a cost-benefit approach to strategy selection is the ability to maintain the concept of calculated rationality (March, 1978), once the costs of executing the decision process are included in the assessment of rationality. Furthermore, because the costs and benefits of various decision strategies will vary across different problems, the cost-benefit perspective provides the potential for explaining a variety of empirical results concerning situation specific decision behavior.

The goal of this paper is to examine the role of effort and accuracy considerations in the adaptive use of different information processing strategies for making a choice. First, an approach to understanding contingent decision behavior using the concept of elementary information processes and the method of computer simulation is introduced, and some prior work by Johnson and Payne (1985) using that approach is briefly discussed. Next, a Monte-Carlo simulation study of the effort and accuracy of choice heuristics in a variety of choice environments which extends the prior work by Johnson and Payne (1985) in several directions is reported. Of particular interest is the impact of time constraints on the relative accuracy of decision strategies. Finally, two experimental studies of task and context effects on decision behavior are reported. As in the simulation, the task variable of interest is the degree of time pressure confronting the decision maker. These studies utilize a new computer-based process-tracing technique to examine the adaptiveness of human choice processes. The degree of correspondence between the efficient strategies identified by the computer simulation for a given type of decision problem and the actual information processing strategies people use is then addressed.

Hence, the major purposes of the paper are threefold: 1) To provide a conceptual approach for modeling effort and accuracy tradeoffs in choice; 2) To report both simulation-based and empirical evidence regarding patterns of adaptivity in strategy selection in different choice environments; and 3) To examine the extent to which the empirical evidence on adaptivity validates the conceptual approach used. As a secondary purpose, the empirical work provides some of the most detailed process-tracing evidence to date regarding responses to time pressure in decision making.

Effort and Accuracy in Choice

One major difficulty in examining strategy selection from a cost-benefit perspective has been the lack of a conceptually appropriate measure of effort that is easy to calculate. A closely related problem is the lack of a common language which could be used to describe the process level similarities and differences among the various choice models that have been proposed. This is important if strategy selection is to be investigated at an information processing level rather than at a more general level of analysis, such as analytic vs. nonanalytic (Beach and Mitchell, 1978) or analytic vs. intuitive (Hammond, 1986). A second area of concern with the cost-benefit approach has been the lack of agreement on how to measure accuracy of choice. Johnson and Payne (1985) have proposed solutions to these problems.

Measuring Strategy Effort. Building on earlier work by O. Huber (1980), Johnson (1979), and the ideas of Newell and Simon (1972), Johnson and Payne (1985) suggest that decision strategies can be decomposed into elementary information processes (EIP's). A decision strategy or rule could then be thought of as a sequence of events, such as reading the values of two alternatives on an attribute, comparing them, and so forth. A possible set of EIP's for decision making, similar to those suggested by Huber (1980) and Johnson (1979), is listed in Table 1. One advantage of this approach is that the EIP's provide a common language for describing seemingly diverse decision strategies in terms of their underlying components.

Insert Table 1 about here

A second advantage of this approach is that a count of the total number of elementary information processes required by a given strategy to reach a decision in a particular choice task environment can be used as a measure of th effort associated with the use of that decision strategy in that task environment (Johnson and Payne, 1985). Examples of the use of EIP counts to measure processing load can be found in a number of studies of cognition (e.g., Card, Moran, & Newell, 1983; Carpenter & Just, 1975).[1]

Measuring Accuracy. Accuracy of choice can be defined in many ways. At a very general level, quality of choice can be defined by basic principles such as consistency in preference. For example, maintaining transitivity, or the avoidance of errors such as selecting a dominated alternative, are often suggested as normative decision principles. However, more specific criteria for decision quality can be developed in certain choice environments. In the area of risky choice, for instance, the expected utility model, which can be derived from certain principles of consistency, is often suggested as a normative decision procedure. A special case of the EU model, the maximization of expected value, has been used as a criterion to investigate the accuracy of decision heuristics through computer simulation (Thorngate, 1980). In the domain of nonrisky choice, the compensatory multi-attribute utility (MAU) rule is often used as a criterion for decision effectiveness (e.g., Zakay & Wooler, 1984).

Examining Accuracy and Effort in Choice. Johnson and Payne (1985) examined both the effort and the accuracy of six decision rules for risky choice. Effort was measured in terms of EIP's, and accuracy was measured both in terms of consistency in choice and EV maximization. The six decision rules examined by Johnson and Payne differed markedly in the amount of the available information they considered. *A priori*, this was expected to be an important determinant of both the accuracy and the effort resulting from their use. The *expected value* (EV) rule, which is based on complete search of the available information, was at one extreme. The *equiprobable* heuristic is similar to the EV rule in that it examines all the alternatives and all outcomes. However, it ignores one of the two attributes of a gamble's outcomes, probability, explicitly treating all events as equally likely. The *most-likely* heuristic, in contrast, examines only one outcome for each alternative, the outcome with the highest probability of occurrence, and selects the alternative with the largest payoff for this outcome. The *maximin* heuristic ignores probabilities entirely and selects the alternative with the largest minimum payoff. *Elimination by aspects* (EBA) is a choice rule proposed by Tversky (1972). A special version of EBA investigated by Thorngate (1980) that attends only to payoff information was also examined by Johnson and Payne. Each payoff of a gamble is compared to a cutoff equal to the mean payoff. If a payoff is less than the cutoff, the gamble is eliminated from further consideration. The rule terminates when either (a) one alternative remains, or (b) all attributes have been considered, and one must choose randomly from the remaining alternatives. Finally, the random choice rule served as a baseline, simply choosing an alternative at random with no search.

Johnson and Payne conducted a series of Monte Carlo studies that varied several aspects of the choice environment. The task variables - number of risky alternatives and number of outcomes- were varied at levels of 2, 4, and 8. Another aspect of the choice environment varied was a context variable, the amount of variance in probabilities within each gamble. This variable was chosen because Thorngate (1980), using a simulation approach, had suggested that probability information may be relatively unimportant in making accurate risky choices. However, Thorngate's method for constructing gambles ensured that the variance in the probability distribution would be small relative to the variance in payoffs. Hence, Johnson and Payne implemented an additional method of probability generation that produced larger variances in the probability distributions. Finally, the presence or absence of dominated alternatives in a choice set was the second context variable examined.

The Johnson and Payne simulations identified choice rules that appeared to provide approximately the accuracy of normative procedures while requiring substantially less effort. The results, however, were highly contingent upon characteristics of the choice environments. In the environment that closely resembled Thorngate's, for example, the equiprobable rule appeared quite accurate. It was also a rule that maintained roughly the same accuracy as the number of outcomes was increased. In contrast, when the variance of the probabilities was increased, the most-likely heuristic became the most accurate, whereas the equiprobable heuristic displayed a marked decrease in accuracy. Furthermore, the most-likely rule was the only one to maintain accuracy as the number of outcomes increased in the high-variance environment. Thorngate's earlier statement about the importance of probability information, therefore, was found to be of limited generality.

Another interesting result was the effect of the presence or absence of dominated alternatives. The removal of dominated alternatives reduced the accuracy of some heuristics to almost chance levels.. Finally, Johnson and Payne also found that task effects tended to have a greater influence on the effort required by strategies, while context effects tended to have a greater influence on accuracy.

Johnson and Payne concluded that heuristics could be highly accurate, but that no single heuristic would do well across all contexts. Instead, if a decision maker wanted to maintain a high level of accuracy with a minimum of effort, he or she would have to choose among a repertoire of strategies, contingent upon situational demands. In other words, a decision maker striving to minimize both errors and effort would have to be highly adaptive in the use of decision processes.

Thus, the Johnson and Payne simulations, using EIP's to measure effort and various criteria for assessing accuracy, were able to yield interesting and important conclusions about adaptivity in choice. However, this work also raised two very important issues. First, the original Johnson and Payne (1985) work investigated a few decision rules in one particular type of risky decision environment. Hence, one issue is whether these results generalize to other rules and different types of choice settings. Second, the simulation work helps to identify adaptive strategies for decision makers, assuming that they wish to minimize either errors, effort, or some combination of the two.

A major unanswered empirical question is the degree to which human decision makers actually display such adaptivity to either errors or effort. The remaining sections of the paper examine these two issues, utilizing further computer simulation for the first and two experiments for the second.

Study 1: A Monte-Carlo Simulation of Effort and Accuracy in Choice

The purpose of this study was to investigate the generality of the Johnson and Payne (1985) simulations by extending both the range of decision strategies and choice environments studied. This study examined a set of ten decision strategies, four more than investigated by Johnson and Payne (1985). Forms of the lexicographic and elimination-by-aspects strategies are included that are more consistent with those originally described by Tversky (1969; 1972). In addition, several strategies not considered in the earlier simulation and two strategies are that are combinations of other strategies (e.g., an EBA rule plus an additive rule) are examined. The specific strategies used are described in more detail below.

A second major change involves the decision task. In contrast to the earlier simulations, the choice alternatives are constructed to have a set of outcomes which have the same probability for each alternative. In other words, each of the alternatives may have a different value for each outcome, but the probability of receiving each outcome is the same for all the alternatives. This allows us to also interpret the current decision task as a riskless choice task, in which the probabilities function as attribute weights that apply across alternatives. Under a riskless interpretation, one can look at a probability of .25, for example, as the weight given to a particular attribute across all alternatives. Alternately, under a risky choice scenario, the .25 is the probability of obtaining that outcome. In previous simulation work (Thorngate 1980, Johnson and Payne, 1985), the probabilities varied across alternatives, preventing the extension of the results to riskless choice. This relationship between risky choice problems and multi-attribute decision problems is discussed more fully in Keeney and Raiffa (1976).

Finally, in addition to the task and context variables studied in the earlier simulation, the present study investigates the impact of time pressures upon decision strategies. Time pressure is potentially one of the most significant task variables. Under time constraints, a heuristic like EBA (Tversky, 1972) might be more accurate than a strategy such as maximization of expected value. The reason is that the rate at which a heuristic's accuracy degrades under increasing time pressure may be slower than the rate at which a more comprehensive processing rule, e.g., EV., degrades. One possible reason for this is that heuristics require fewer operations and will generally be "further along" when time runs out. Furthermore, time pressure relates to the extent to which people use heuristics because they have no other choice (Simon, 1981). A more normative decision strategy like expected utility maximization may exceed the information processing capabilities of a decision maker, given any "reasonable" time limit for making the decision. If use of a more normative rule is effectively impossible, then the task of deciding how to choose becomes a selection of the "best" among a set of available heuristics, not a decision on whether to use some heuristic or the more normative rule.

Decision Strategies

The ten decision strategies were implemented using the EIPs and production system representation proposed by Johnson and Payne (1985). The ten decision strategies varied substantially in the amount of the available information used to make a choice. The most information intensive was a version of a Weighted Additive (WADD) compensatory process. This strategy considers the values of each alternative on all the relevant attributes (outcomes) and all the relative importances (weights or probabilities) of the different attributes (outcomes) to the decision maker. The rule develops a weighted value for each attribute by multiplying the weight times the value and sums over all attributes to arrive at an overall evaluation of an alternative. Then the alternative with the highest evaluation is selected. Thus, the weighted additive rule selects an alternative based on an exhaustive search of the available information. Such a process is often suggested as a normative procedure for multiattribute choices (Ulvila & Brown, 1982). In contrast, the Random (RAN) choice rule chooses an alternative at random with no search of the available information. Hence, the Random rule serves as a minimum baseline for measuring both accuracy and effort.

In addition to these two baseline rules, six individual heuristics for multiattribute choice were implemented, along with two combination strategies. The Equalweight (EQW) rule examines all alternatives and all attribute values for each alternative. However, the rule ignores information about the relative importance of each attribute. Instead, the equalweight rule operates by summing the attribute values for each alternative to get an overall value, and the alternative with the highest total is selected. In some contexts, the equal weight rule has been advocated as a highly accurate simplificaton of the choice process (Dawes, 1979; Einhorn and Hogarth, 1975). The equal weight rule is identical to the equiprobable rule for risky choice investigated by Thorngate (1980) and Johnson and Payne (1985). The Elimination by Aspects (EBA) rule (Tversky, 1972) begins by determining the most important attribute (the outcome with the highest weight (probability)). Then, the cutoff value for that attribute is retrieved, and all alternatives with values for that attribute below the cutoff are eliminated. This process continues with the second most important attribute, then the third, and so on, until one alternative remains. This version of EBA differs from that examined by Thorngate (1980) and Johnson and Payne (1985). The present version of EBA does order search by attribute importance, so it more closely resembles the EBA model originally proposed by Tversky (1972).

The Majority of Confirming Dimensions (MCD) rule has been suggested by Russo and Dosher (1983). This rule involves processing pairs of alternatives. The values for each of the two alternatives are compared on each attribute, and a running score is kept of how many times each alternative has a better value on an attribute. The alternative with a majority of winning attribute values is selected. In the case of an equal number of winning values for the two alternatives, we implemented a version of this rule where the alternative winning the comparison on the last attribute is retained. The retained (winning) alternative is then compared to the next alternative among the set of alternatives. The process of pairwise comparison repeats until all alternatives have been evaluated and the final winning alternative identified. The Satisficing (SAT) rule (Simon, 1955) does not necessary examine all the alternatives in a set. Instead, alternatives are considered one at a time. For each attribute of an alternative, it is determined whether the attribute value exceeds a cutoff value. If any attribute value is below the cutoff value, that alternative is rejected. The first alternative in a set which has values which pass the cutoffs for all attributes is chosen. That is, a choice can be made before all alternatives have been evaluated. In the case where no alternative passes all the cutoffs, a random selection is made among the alternatives.

We also implemented two versions of the lexicographic choice rule. For the strict Lexicographic (LEX) rule, the most important attribute is determined, and the values of all the alternatives on that attribute are then examined. The alternative with the highest value on that attribute is selected. If there are ties, the second most important attribute is examined, and so on until the tie is broken. However, because the attributes in the simulation are generated as continuous random variates, ties almost never occur. Thus, this rule is essentially the same as the most likely heuristic for risky choice investigated in Thorngate (1980) and Johnson and Payne (1985). We also examined a Lexicographic Semi-Order (LEXSEMI) rule (Tversky, 1969). This rule is similar to the strict lexicographic rule, but introduces the notion of a just-noticeable difference (JND). If several alternatives are within a JND difference of the best alternative on the most important attribute, they are considered to be tied. These alternatives are compared on the next most important attribute, and the process continues until one option remains. The potential advantage of the Lexicographic semi-order rule is that it ensures that an option which is marginally better on the most important attribute but much worse on other attributes will not necessarily be selected.

Finally, two combined strategies were implemented. The first was an Elimination-by-Aspects plus Weighted Additive (EBA+ADD) rule. This rule used an EBA process until the number of available alternatives remaining was three or less, and than used a weighted additive rule to evaluate the remaining alternatives and select the best. The other combined strategy used Elimination-by-Aspects plus Majority of Confirming Dimensions (EBA+MCD). This rule again used an elimination-by-aspects process to reduce the problem size to three alternatives or less, and then a majority of confirming dimensions heuristic is used to select the winning alternative from the reduced set.

These combinations were used because they had been observed in several previous choice process studies (e.g., Payne, 1976; Bettman and Park, 1980).

In addition to the amount of information utilized, these heuristics differ in how information about the alternatives and attributes of a decision problem is likely to be processed. Some of the rules imply an alternative-based form of processing. That is, information is processed regarding the multiple attribute values of a single alternative before information about a second alternative is processed. Examples of such rules are the weighted additive rule, the equalweight rule, and satisficing. Other decision rules imply an attribute-based form of processing. That is, information is processed regarding the values of several alternatives on a single attribute before information about a second attribute is processed. Examples of attribute-based processing strategies are the EBA rule and the lexicographic choice rules. The distinction between alternative-based (also called "holistic processing") and attribute-based decision strategies has played a major role in numerous discussions of decision models (e.g., Bettman, 1979; Goldstein, 1986; Svenson, 1979), and has implications for the robustness of the various strategies under time constraints. In particular, it can be argued that under increasingly severe time pressure, it becomes more and more important to examine all alternatives, even if on a limited set of attributes. Thus, attribute-based strategies may have an advantage (i.e., degrade more slowly) under time pressure.

Task and Context Variables

For purposes of comparison with Johnson and Payne (1985), we included essentially the same set of task and context variables. We manipulated task complexity through variations in the number of alternatives and number of attributes. The numbers of alternatives were 2, 5, and 8; the numbers of attributes were also 2, 5, and 8.

One context variable was the presence or absence of dominated alternatives. Removing dominated alternatives produces efficient or Pareto-optimal choice sets. The other context variable was the variance in the relative weights assigned to the attributes. As noted earlier, Johnson and Payne (1985) found that the variance of the probabilities impacted on which heuristics were most efficient in risky choice. As before, we examined both low variance and high variance sets of weights. The generation of the weights paralleled the two procedures used in Johnson and Payne (1985) for generating the probabilities of outcomes, with the difference that only one set of weights were generated for a given choice problem.

Time Constraints

One new task variable was added, time pressure. Four levels of time constraint were investigated. One level involved no time pressure. A given rule could use as many operations as needed. The three other levels of time constraint were a maximum of (1) 50 EIP's (severe time pressure), (2) 100 EIP's (moderate pressure), and (3) 150 EIP's (low pressure). These time (EIP) constraint values were selected on the basis of an analysis of the maximum number of EIP's associated with the most effortful rule (weighted additive).[2] Note that the total number of EIP's was used to operationalize time pressure. This implicitly assumes that each EIP takes a similar amount of time. While this is clearly an oversimplification, equal weighting of EIP's was felt to be a useful initial approximation.

A key issue in dealing with the time or effort constraints is how rules should select among alternatives if they run out of time. For those rules where one alternative which is best so far is available (i.e., the WADD, EQW, and MCD rules), that alternative was selected. The EBA, lexicographic, and satisficing rules all picked an option randomly from those alternatives that had not yet been eliminated. For the two combined strategies, the selection was either made at random from the alternatives not yet eliminated, if the combined strategy was still in the EBA phase, or the best so far if in the WADD or MCD phase.

JNDs and Cutoff Values

Three of the rules, elimination-by-aspects, satisficing, and the lexicographic-semiorder rule, involve parameters that affect the potential effort and accuracy of the rules. For EBA and satisficing , this is the cutoff value used to eliminate alternatives. For the lexicographic-semiorder rule, it is the value of the JND. While these parameters are, in some sense, under the control of the decision maker for each decision, we wanted to establish a priori values which would be the same for all decisions made by the simulation. Other alternatives, such as finding an optimal level of the cutoff or JND for each decision or decision environment, would themselves require effort on the part of the decision-maker, and would have to be captured in the simulation. Instead, we ran a pilot simulation without any time constraints. All attributes in the simulation were drawn from a uniform distribution bounded by 0 and 1000. We manipulated both cutoffs (100, 300 and 500) and JNDs (1, 50, and 100) and selected values which represented the most efficient accuracy-effort tradeoffs across the entire set of decisions. We found that values of the cutoff of 500 and 300 were most efficient for elimination-by-aspects and satisficing, respectively, and that a JND of 50 gave the best performance for the lexicographic-semiorder rule. We therefore set the JND value at 50, and included cutoffs set at 300 and 500 as a factor in the experimental design. Since this cutoff effect is small, compared to other factors, we shall not discuss it further. When the results for the EBA and satisficing rules are presented, they are for the most efficient cutoff values for each rule.

Method

Each of the ten decision rules was applied to 200 randomly generated decision problems in each of the 288 conditions defined by a 3 (number of alternatives) by 3 (number of attributes) by 2 (low or high variance of weights) by 2 (presence or absence or dominated alternatives) by 2 (cutoff values) by 4 (time constraints) factorial. After each trial, the alternative selected was recorded, along with a tally for each elementary operation used by the decision rule. Johnson and Payne (1985), for comparison, investigated only 36 possible task and context combinations. For further details of the simulation methodology, see Johnson and Payne (1985).

Results

The measure of accuracy used compares the relative performance of strategies to the two baseline strategies: (1) the weighted additive (WADD) value, and (2) random choice. The measure is defined by the following equation:

$$\text{Relative Accuracy} = \frac{\text{WADD}_{\text{heuristic rule choice}} - \text{WADD}_{\text{random rule choice}}}{\text{WADD}_{\text{additive rule choice}} - \text{WADD}_{\text{random rule choice}}}$$

That is, we determined the maximum weighted additive (WADD) value possible in a particular choice set, and the WADD value associated with a random selection. The WADD value of the alternative selected by a decision heuristic is then compared to these two baseline values. This measure of performance is bounded by a value of 1.00 for the WADD rule itself, and 0.0 for random selection. It thus provides a measure of the relative improvement over random selection (Johnson and Payne, 1985).

Effort was measured by first summing the total number of elementary operations used by a decision rule to make a selection from a particular set of alternatives. This measure assumes that each elementary operation requires essentially the same level of time or mental effort. This assumption was used by Johnson and Payne (1985) in their principal analyses.

Table 2 presents the relative accuracy scores and the unweighted effort scores for each of the ten decision strategies, in each of the four variance in weights (low, high) by dominance (present or absent) context conditions. These scores are for the no time pressure conditions. The results are averaged over number of alternatives and attributes and cutoffs, except that the results for the EBA and satisficing rule are for each rule with its "best" cutoff value.

Table 3 presents the relative accuracy of each decision strategy in the four context conditions under the three levels of time pressure. Effort measures are not included, because they are constrained by the time pressure cutoff values.[3]

No Time Pressure Results

The simulation results for choice among multiattribute alternatives without time pressure, shown in Table 2, are similar to those found by Johnson and Payne (1985). In some environments, heuristics for multiattribute choice can approximate the accuracy of a normative strategy (WADD), with substantial savings in effort. A decision maker using an equal weighted version of the additive model (EQW), for example, can achieve 89% of the relative performance of the normative model, with only about half the effort, in the low-variance, dominance-possible task environment. Even more impressive is the performance of the strict lexicographic rule in the high-variance task environments. The lexicographic rule achieves 90% relative accuracy, with only about 40 percent of the effort, on average. Note that the lexicographic-semiorder rule is slightly better than the simpler lexicographic rule in only one of the four decision environments. The extra effort needed to take into account just-noticeable differences may only be of value for a limited set of decision situations.

As was found in Johnson and Payne (1985), it is clear from Table 2 that the most efficient heuristic varies across decision environments. It is also clear that some heuristics (e.g., MCD and Satisficing) perform reasonably in the dominance-possible environments, but are very poor choice rules in tasks where all dominated alternatives have been screened out.

Insert Table 2 about here

One interesting result from Table 2 is the relatively efficient performance of the elimination-by-aspects rule. In the earlier work by Thorngate (1980) and Johnson and Payne (1985), the version of EBA investigated did not show much accuracy (30% on average). In the present simulation, the EBA rule provided an average relative accuracy value of 65% over all task environments, with an effort score of 85 versus 160 for the WADD rule. Obviously, allowing the EBA rule to search as a function of the relative importance of attributes (one main difference between the current implementation and the previous studies) makes a major difference in the accuracy of an EBA rule.

Another interesting set of results concerns the performance of the two combined decision strategies. The combination of an elimination process with a weighted adding model (EBA+ADD) performed well across all task conditions.

That rule appears to offer a good combination of accuracy and reasonable levels of effort. The EBA+MCD rule, on the other hand, does not appear to be an efficient combination strategy. On the basis of the overall simulation results, it appears that the EBA rule alone is superior to the EBA+MCD rule.

Time Pressure Results

From the time pressure results, shown in Table 3, it is clear that time constraints have different effects on the various rules. The weighted additive rule, for example, shows a marked reduction in accuracy from the baseline value of 1.0 for the no time pressure condition to an average accuracy of only .2 under the most severe time constraint in the no dominance-low variance condition. In contrast, the elimination-by-aspects heuristic shows relatively little effect of time pressure. The average accuracy is reduced from .69 (no time pressure) to .56 (severe time pressure). Interestingly, the EBA rule is actually the most accurate decision strategy for three of the four choice environments for severe time pressure. Another rule that appears to hold up well under time pressure is the lexicographic rule. In general, it appears that strategies involving an initial processing of all alternatives across a limited set of attributes do well under time pressure. On the basis of the simulations, what seems to be important in time pressured decision environments is to use a choice strategy that involves the processing of at least <u>some</u> information about <u>all</u> alternatives as soon as possible. However, note that at least in one decision environment (dominance-possible, variance in weights-low), the alternative simplification strategy provided by the equalweight rule does well under even the most severe time constraint studied.

Insert Table 3 about here

Note also the effects of time pressure on the relative performance of the EBA and the EBA plus weighted additive rules. Under most conditions, the combined strategy is more accurate. However, under severe time pressure, the strict EBA rule does better. We speculate again that under severe time pressure, the processing of at least some information about all alternatives is important. With the combined rule, some alternatives may not be processed when the initial number of alternatives is small. With a small number of alternatives, the rule becomes essentially a weighted additive rule.

Overall, the results show that some decision strategies are much more sensitive to time constraints than others. What appears important under severe time pressure is to do at least a quick, if dirty, evaluation of all the alternatives. This type of strategy seems superior to one that evaluates some alternatives more completely, but may not evaluate some other alternatives at all within the time constraint. A related finding is that those strategies which involve attribute-based processing (e.g., LEX & EBA) appear to hold up better under time pressure than alternative-based processing strategies, e.g., WADD and EQW.

Study 2: Time Pressure and Context Effects on Decision Processes

Taken together, the simulation results from Study 1 and the earlier work of Johnson and Payne (1985) indicate what a decision maker might do to adapt to a decision environment. Specifically, this work suggests the possibility that a decision maker might be able to maintain a high level of accuracy and minimize effort by using a diverse set of heuristics, changing rules as contexts and time pressure change.

In this and the following study, we examine the degree of correspondence between the actual adaptivity shown by human decision makers and the adaptive strategies indicated by the simulation results. Specifically, we ask: (1) To what extent do people change strategies as a function of task effects such as time pressure and context effects such as the variance in probabilities?; and (2) Are these changes in strategy adaptive in the directions suggested by the simulation? Two empirical studies which monitor subjects' decison processes as we manipulate both time pressure and the variance in probabilities were carried out to answer these questions.

The simulation results provide a fairly clear picture of an adaptive decision maker. Consider the context manipulation of the variance in probabilities, and assume that dominated alternatives are possible. Then, if decision makers are adaptive in the way the simulations suggest, we would expect to see a relationship between the variance in probabilities and the amount of alternative-based versus attribute-based processing. The simulation indicates that an alternative-based processing strategy, the equalweight rule, is a very accurate heuristic for low-variance decision environments. On the other hand, a more attribute-based processing strategy, the lexicographic rule, is more accurate in high variance in probabilities decision environments. Note that a shift in the form of processing as a function of context would indicate that people are sensitive to changes in choice environments due to a concern for accuracy and not due to task complexity or information processing demands. The reason is that the accuracy of these rules varies across contexts (variance conditions), but the effort required by the rules does not. Studies showing contingent processing due to task complexity (e.g., changes in numbers of alternatives and attributes) are common; studies showing processing changes due to changes in context variables, and hence implicitly a concern for accuracy, are rare (cf. Payne, 1982).

The task variable examined is the presence or absence of time pressure. We also expect strategy changes at severe levels of time pressure. As the simulation results indicate, the most accurate decision rule, the weighted additive rule, becomes less accurate than several choice heuristics when there is severe time pressure. Consequently, the presence of an explicit time constraint should emphasize the adaptive use of choice heuristics. In particular, the simulation results indicate that attribute-based forms of processing, and specifically the EBA strategy, maintain relatively high levels of accuracy under time pressure, particularly in the high variance context. This suggests that the frequency with which attribute-based processing occurs should increase with time pressure.

Time pressure is interesting for other reasons as well. Many real-world decisions are made under conditions of moderate to severe time constraints. Given the potential importance of time pressure to decision making, it is surprising how few empirical studies have directly examined the influence of time constraints on judgments and choices (see Svenson, Eckland, & Karlson, in press). The best known work in this area is by Peter Wright (Wright, 1974; Wright & Weitz, 1977). Wright (1974) contains many of the theoretical concepts that have driven most subsequent time pressure research; he equated variations in time pressure with other ways one might vary task complexity and then argued that increased time pressure would lead to efforts by the decision maker to simplify the task.

Ben Zur and Breznitz (1981) identified at least three ways in which this simplification could occur. One way to cope with time pressure is to process only a subset of the most important information. This idea has been referred to as "filtration" (Miller, 1960). Another way to cope with time pressure is the "acceleration" of processing (Ben Zur & Breznitz, 1981; Miller, 1960).

That is, one tries to process the same information, but at a faster rate. Finally, one could shift processing strategies. At the extreme, this could involve random choice, or what has been called "avoidance" (Ben Zur & Breznitz, 1981; Miller, 1960). A less extreme form of contingent processing would involve a shift from a more effortful rule, like the additive rule, to a less effortful rule, like EBA. The simulation results presented earlier indicate that such a shift in strategy could maintain relatively high levels of accuracy even under severe time pressure.

The hypothesis of filtration is supported in the literature. For example, Wright (1974), Wright and Weitz (1977), and Svenson et. al. (in press) all report that the most important information in a judgment task was given more weight under time pressure. Ben Zur and Breznitz (1981), in the only process tracing study of time pressure effects on choice, also report some shifting to the use of more important information under time pressure. Furthermore, Ben Zur and Breznitz found that subjects spent less time looking at individual items of information under time pressure. They concluded that the combination of filtration and limited acceleration "can be viewed as the optimal decision making strategy when the DM is confronted with information overload while pressured by deadlines (p. 102)".

The question of optimality of choice under time pressure was directly addressed by Zakay and Wooler (1984) and Zakay (1985). They found that under time pressure a smaller proportion of the observed choices consisted of the alternative that had been measured as having the greatest additive value.

In much of the work on time pressure effects, a hypothesis is that time pressure will cause people to shift toward "simpler" decision strategies. However, almost all of the prior studies of time pressure have used input-output analyses. As Wright (1974) correctly points out, the use of correlational techniques based on inputs and outputs by themselves is generally not adequate to demonstrate a shift in processing strategy. To our knowledge, there is no process evidence for strategy shifts under time pressure. Consequently, the present study uses the process tracing technique of monitoring information acquisition to test the adaptiveness of actual decision processes to different time constraints. The study also examines the adaptiveness of decision processing to the context variable associated with the distribution of probabilities (weights) defining the options in a choice set. While the major purpose of the study is to study adaptivity of decision making, the specific results for time pressure are also of great interest in and of themselves.

Method

Subjects. Sixteen undergraduates at Duke University served as subjects in this experiment. Participation in the experiment earned credit toward fulfillment of a course requirement. In addition, the subjects had a possibility of winning as much as $9.99, depending on their actual choices.

Stimuli. The stimuli were sets of risky options. Each set contained four options. Each option in a set offered four possible outcomes. The outcomes involved possible payoffs ranging from $.01 to $9.99. Every option in a set was defined in terms of the same four outcome probabilities. That is, each choice alternative was defined in terms of the same four possible states of the world. The probabilities for any given state of the world ranged from .01 to .96, with the constraint that the sum of the four outcome probabilities equaled 1.0.

The values of the options were generated using the techniques contained in the simulation program described in Johnson and Payne (1985) and used in Study 1. Ten sets of high variance in probabilities (weights) options and 10 sets of low variance options were generated. Dominated options were allowed in all sets. In terms of the design used for Study 1, we sampled sets of options from the low-variance, dominance-possible, and high-variance, dominance-possible conditions. The probability (weight) and payoff values for a sample of three sets of low variance options and three sets of high variance options used in this study are provided in Table 4. Overall, the sets of options in the Low and High variance conditions were similar in terms of their average expected vlaues.

As noted above, these decision environments are ones where heuristics can be highly efficient, but which heuristic is best differs across decision environments. The equiprobable or equal weighted additive rule, characterized by an alternative-based form of processing, does well in the low variance condition. In contrast, the lexicographic rule, characterized by an attribute-based form of processing, does better than the equalweight rule in the high variance condition. We expect in general that adaptive information processing by an individual would involve a shift from more alternative-based processing to more attribute-based processing as the variance in probabilities or weights that characterize the options in a choice set increases.

Insert Table 4 about here

The 20 sets of options (10 low variance, 10 high variance) were presented under two time pressure conditions. The first was no explicit time pressure at all. Subjects were told that they could take as much time as they wished to acquire information about probabilities and payoffs and make a decision. The other condition involved a 15 second time constraint.[4] In this condition, a clock was shown in the upper left-hand corner of the display showing the information about the gambles (described more fully below). As the 15 seconds passed, the clock slowly disappeared. At 15 seconds, a beep sounded, the subject could not acquire additional information, and he or she was instructed to make a choice.

There were 40 decision problems (2 context conditions x 2 time pressure conditions x 10 replications), presented to each subject in a random order. The use of a complete within-subjects design was motivated by the desire to provide the strongest possible test of adaptive decision making (i.e., that the same subject would be expected to switch strategies from one trial to the next). A complete experimental session took from 30-45 minutes for each subject.

The Mouselab methodology. Information acquisitons, response times, and choices were monitored using a new software system called Mouselab (Johnson, Payne, Schkade, & Bettman, 1986). This system uses an IBM personal computer, or equivalent, equipped with a "mouse". A mouse is a hand-controlled pointing device that can be used to move a cursor around the display screen of the computer. The stimuli are presented on the display in the form of a matrix of available information. The first row of boxes contained information about the probabilities of the four outcomes. The next four rows of boxes contained information about the payoffs associated with the different outcomes for each alternative, respectively. At the bottom of the screen were four boxes that were used to indicate which alternative was most preferred. Figure 1 is an example of a stimulus display with one box opened, and with the time pressure clock part way through the countdown.

Insert Figure 1 about here

When a set of options first appears on the screen, the values of the payoffs and probabilities are "hidden" behind the labeled boxes. To open a particular box and examine the information, all a subject has to do is move the cursor into the box. The box immediately opens and remains open until the cursor is moved out of the box. Only one box can be open at a time.

The Mouselab program records the order in which boxes are opened, and the amount of time boxes are open. When the subject is ready to make a choice, he or she just moves the cursor into the choice box representing the preferred alternative and pushes one of the buttons on the mouse. After the program verifies that the subject has indeed selected his or her preferred alternative, the response is recorded, along with the total elapsed time since the display first appeared on the screen. Response times are recorded to an accuracy of 1/60th of a second.

The Mouselab methodology comes close to the recording of eye movements in terms of speed and ease of acquisitions, while minimizing instrumentation cost and difficulty of use for both subject and experimenter. An analysis of the time necessary to move the mouse between boxes in our displays using Fitts Law indicates that one could move between boxes in less than 100 milliseconds. This suggests that the time to acquire information using the Mouselab system is limited mainly by the time it takes to think where to point, rather than by the time it takes to move the mouse. More details on the Mouselab system can be found in Johnson, Payne, Schkade, and Bettman (1986). By using the data collected with the Mouselab system, numerous summary measures describing the subject's decision process can be developed. Several such measures are outlined in the results section.

Procedure. Each subject was told that the purpose of the experiment was to understand how people make decisions. They were told that there were no "right" or "wrong" answers.

The subjects then were instructed on the use of the Mouselab information acquisition system and allowed to practice its use. Next they were told that they would be presented with a series of decisions involving choices among risky options. They were told that some decisions would involve an explicit time constraint, while for other decision problems they could take as long to respond as they wished.

To increase motivation, the subjects were told that at the end of the experiment a decision problem would be selected at random, and the option they had chosen would be played by randomly generating an outcome according to the probabilities for that option. They would be allowed to keep whatever money they won.

Results

Overview. Our main focus in the results is how people adapt to the task manipulation, time pressure, and the context manipulation, variance in probabilities. We consider effects on how subjects processed information, relative accuracy levels, and the relationship between processing strategy and accuracy. Before considering these results, we first introduce measures used to characterize the form of information processing. Then these measures are examined in terms of both time pressure and context effects. Next, the impact of time pressure and context on the relative accuracy of decisions will be discussed. Finally, the relationship between processing measures and accuracy will be examined to see how it varies over both the time pressure and context conditions.

A key hypothesis of this study is that people will adapt their behavior to the demands of the decision environment in a fashion consistent with the results of the simulations. As noted, to provide the strongest possible test of adaptiveness, we utilized a within-subjects experimental design. Subjects, however, may have to experience several examples of different types of decision problems before settling on a preferred decision strategy for a particular type of problem. Consequently, we present the results calculated both for the block of 20 decision problems seen first by the decision maker, and the block of the last 20 decisions (Recall that the sets of options representing the four combinations of time pressure and context were presented in a random order to the subjects, so that problems corresponding to each of the four time pressure-variance combinations were distributed essentially equally over the two blocks).

Process measures. Information acquisition behavior can be characterized in a wide variety of ways. One can examine the amount of information acquired, the sequence of information acquired, and the time spent acquiring information (See Klayman (1983) for a discussion of various information acquisition measures). For the purposes of this paper, we adopt eight measures of decision processes. The first measure is the total number of times information boxes were opened for a particular decision. This is one measure of the total amount of search, denoted acquisitions (ACQ). A second measure of total amount of search is the total time spent looking at information in all the opened boxes (BOX TIME). A third measure, which is directly relevant to the acceleration of processing, is the time spent per item of information acquired (TPERACQ).

The fourth and fifth measures reflect the relative attention devoted to specific types of information in the decision environment. One measure, denoted (PTMI), reflects the proportion of the total box time that was spent in boxes involving the most important attribute of a particular decision problem. We defined the attribute (outcome) with the largest weight (probability of occurrence) as the most important attribute. The other measure, denoted (PTPROB), is the proportion of time spent on probability information as opposed to information about payoff values.

The sixth measure is based on the sequence of information acquisitions. Given the acquisition of a particular piece of information, the next piece of information acquired might involve the same alternative but different attribute (an alternative, holistic, or a Type 1 transition), or the same attribute but a different alternative (an attribute, dimensional, or Type 2 transition).[5] A simple measure of the relative amount of alternative-based (Type 1) and attribute-based (Type 2) transitions is provided by calculating the number of Type 1 transitions minus the number of Type 2 transitions divided by the sum of Type 1 and Type 2 transitions (Payne, 1976). This measure of the relative use of alternative-based versus attribute-based processing ranges from a value of -1.0 to +1.0. A more positive number indicates relatively more alternative-based processing, while a more negative number indicates relatively more attribute-based processing. This measure of sequence of search is denoted (PATTERN).

Finally, the last two measures reflect the variances in the proportions of time spent on each alternative (VAR-ALTER) and each attribute (VAR-ATTRIB), respectively. Note that more compensatory decision rules, e.g., WADD, EQW, and MCD, imply a pattern of information acquisition that is constant (low in variance) across alternatives and attributes. In contrast, heuristic strategies, like EBA, lexicographic, and satisficing, imply more variance in processing across alternatives and attributes.

Table 5 presents the means for each of the eight process measures as a function of time pressure (No Time Pressure vs. 15 sec.), decision context (Low variance vs. High variance), and block of decision problems (1st half vs. 2nd half.). The data were analyzed with three within-subjects factor (time pressure, context, and block) analyses of variance. The results presented in Table 5 will be discussed first in terms of time pressure effects, then context effects, and finally the relationships among time pressure, context, and decision processing will be examined.

Insert Table 5 about here

Time pressure and processing. As would be expected, the subjects acquired fewer items of information (ACQ) in the time constrained choice environments ($M = 35.0$ vs. $M = 16.7$, $F = 378.44$, $p < .01$).[6] Subjects also spent less overall time looking at information (BOXTIME) in the time pressured problems ($M = 25.7$ vs. M 8.1 sec., $F = 324.22$, $p < .01$). Both ACQ ($M = 28.9$ vs. $M = 23.8$, $F = 24.39$, $p < .01$) and BOXTIME ($m = 18.7$ VS. $m = 15.1$, $f = 22.05$, $P < .01$) were also smaller for the last block of 20 decision problems compared to the first block of 20 decision problems. This finding was qualified by block by time pressure interactions for both ACQ ($F = 20.15$, $p < .01$) and BOXTIME ($F = 19.31$, $p < .01$), which simply show that the amount of information acquisition did not vary much over blocks in the high time pressure condition, but that less information was acquired in the second block with no time pressure.

One major hypothesis regarding time pressure and decision making is that people will adapt to time constraints by accelerating their processing of items of information. The results for the time per acquisition variable (TPERACQ) indicate that people did process information significantly faster under time pressure ($M = .67$ vs. $M = .49$ sec., $F = 217.36$, $p < .01$). In addition, time per acquisition was smaller ($M = .60$ vs. $M = .57$ sec., $F = 7.51$, $p < .01$) for the second block of trials than the first, although this was qualified by a block by time pressure interaction ($F = 3.87$, $p < .05$)

showing that the decrease over blocks only occurred in the no time pressure condition. Thus, our results are consistent with those of Ben Zur and Breznitz (1981) concerning the acceleration of processing.

Another hypothesis regarding time pressure, examined by many researchers, concerns the filtration of information. That is, do people focus more on the most important information under time pressure? The proportion of time spent examining items of information involving the most likely outcome (PTMI) in this study was significantly greater under time pressure ($M = .37$ vs. $M = .40$, $F = 9.83$, $p < .01$). There were no effects of block or interactions involving block. Note also that the proportion of time spent on probabilities (PTPROB) was greater for the time pressured problems ($M = .25$ vs. $M = .29$, $F = 18.14$, $p < .01$). The proportion of time spent on probabilities also increased slightly from the first block to the second ($M = .26$ vs. $M = .28$), and there were no interactions involving block. These results clearly support the filtration hypothesis.

Beyond evidence for acceleration and filtration of processing, our results also suggest a shift in information processing strategies as a function of time pressure. Such a shift is crucial evidence for adaptivity. The PATTERN variable, which depicts the extent to which acquisitions are alternative-based or attribute-based, showed an effect of time pressure, with processing becoming more attribute-based under higher time pressure ($M = -.22$ vs. $M = -.28$, $F = 3.55$, $p < .059$) (Recall that more negative values of this variable correspond to more attribute-based processing). There were no main effects or interactions involving block on this variable. The variance in the proportion of time spent processing the various alternatives (VAR-ALTER) showed no effects due to time pressure, although there was a tendency for this variance to increase from the first block to the second ($M = .29$ vs. $M = .32$,

$F = 4.57$, $p < .05$). Finally, the variance in the proportion of time spent processing the attributes (VAR-ATTRIB) showed an effect due to time pressure, with greater variance under high time pressure ($M = .31$ vs. $M = .38$, $F = 5.98$, $p < .05$). This proportion also rose from the first block to the second ($M = .32$ vs. $M = .38$, $F = 12.83$, $p < .01$) and showed a three way interaction between time pressure, block, and variance that is not easily interpretable ($F = 5.57$, $p < .05$). However, the time pressure results are the most crucial here, and it is important to note that the shift in information processing behavior is in a direction that is consistent with greater use of attribute-based heuristic rules under time pressure. There is more attribute-based processing and more variance in processing in the time constrained decision problems.

To summarize, we found evidence that people adapted to time pressure by accelerating processing, focusing processing, and by changing the pattern (strategy) of processing toward more attribute-based heuristics.

Context effects on processing. The context variable (Low variance in probabilities versus High variance in probabilities) also had a significant effect on a variety of process measures. BOXTIME ($M = 19.2$ vs. $M = 14.6$, $F = 31.02$, $p < .01$), ACQ ($M = 28.9$ vs. $M = 23.8$, $F = 36.39$, $p < .01$), and time per acquisition ($M = .60$ vs. $M = .57$, $F = 7.21$, $p < .01$) were all significantly less for problems involving a higher degree of variance in probabilities. These effects were all qualified by significant variance by time pressure interactions, showing that the decrease due to higher variance in probabilities was manifested only in the low time pressure condition ($F = 21.36$, $p < .01$, $F = 12.91$, $p < .01$, and $F = 12.56$, $p < .01$ respectively). In addition, there was more focus on the largest probability (PTMI) when there was high variance in probabilities ($M = .34$ vs. $M = .44$, $F = 92.34$, $p < .01$), although there was no significant difference in the proportion of time spent on probabilities ($F = 1.34$, n.s.). There were also no interactions involving variance for the latter two variables.

The largest impact of the context manipulation was on the processing variables: PATTERN, VAR-ATTRIB, and to a lesser extent VAR-ALTER. The predominant pattern of processing became significantly more attribute-based for the high variance gamble sets ($M = -.12$ vs. $M = -.37$, $F = 54.60$, $p < .01$). The variance in the proportion of time spent on attributes was also much greater for the high variance option sets ($M = .22$ vs. M $.49$, $F = 119.13$, $p <$ $.01$). Finally, there was more variance in processing across alternatives when the decision problems involved probabilities that differed greatly ($M = .28$ vs. $M = .33$, $F = 6.83$, $p < .01$). There were no two-way interactions involving the context manipulation for these three dependent variables.

As noted earlier, the simulations suggest that changes in a context variable, such as the variance of the probabilities associated with the options in a choice set, do not alter the effort levels of decision strategies. On the other hand, the accuracy of strategies is strongly affected by context in these simulations. Prior work investigating contingent decision processing has demonstrated that decision makers are influenced by task variables that impact effort (e.g., number of alternatives). The present results clearly demonstrate that people will also shift processing strategies with variations in context variables that impact on the potential relative accuracy of heuristics, but not on their relative effort. Such context effects have rarely been shown.

In sum, the results for both the time pressure (task) manipulation and the variance (context) manipulation indicate that people adapt their decision processes to changes in the decision environment impacting on both the relative effort and the relative accuracy of choice heuristics.

Accuracy of choice. As noted in our discussion of the Monte-Carlo simulation experiment, there are a number of ways in which accuracy or quality of choice can be measured. For consistency with the prior simulation work on accuracy of heuristics (Thorngate, 1980; Johnson & Payne, 1985), we used a measure of accuracy based on the maximization of expected value (EV). The main advantage of EV as an accuracy measure is that values from individual decision makers are not required to operationalize the rule. Of course, a maximization of EV criterion is at best only a first approximation to the optimal choice, since it does not reflect individual differences.

The primary measure of accuracy we used is essentially the same as the relative performance measure of accuracy used in Study 1. That is, as above we defined a measure that is a measure of the proportion of the maximum possible improvement in EV obtained over that which would be expected based on a random choice rule. The closer the value of relative accuracy is to 1.0, the nearer the responses are to a strict maximization of expected value rule.

The average relative accuracy scores for the 16 subjects as a function of time pressure, variance in probabilities, and decision block are presented in Table 6. While the relative accuracy scores are higher under no time pressure ($M = .62$ vs. $M = .48$, $F = 8.32$, $p < .01$) and in the second block ($M = .48$ vs. $M = .62$, $F = 7.23$, $p < .01$), it is clear from Table 6 that the decrement in performance is concentrated in the responses to the earlier (first block) problems involving time pressure. By the latter block, people had adapted to time pressure and had improved their performance to levels similar to those obtained in the no time pressure condition. This is verified by the significant block by time pressure interaction ($F = 10.73$, $p < .01$).

Insert Table 6 about here

Relationship of Process to Accuracy. A major conclusion reached from the Monte-Carlo simulations of effort and accuracy in choice was that a decision maker who used heuristics would have to adaptively choose among decision strategies, depending upon the specific choice environment. The prior results for process measures and accuracy measures indicate that subjects in this experiment were influenced by both the task and context variables. A major question is whether the adaptiveness in terms of process is related to improvements in accuracy. Table 7 presents results that address that question.[7] The process variable used in Table 7 was the relative amount of alternative-based versus attribute-based processing (i.e., PATTERN). Recall that higher values of that variable correspond to more alternative-based processing. The accuracy measure was the relative accuracy score. It is clear from Table 7 that the relationship between pattern of processing and performance was stronger for the second block decision problems. It is also clear that under no time pressure, there is a significant relationship between relative accuracy and the use of relatively more alternative-based processing. That result might be expected, given that the relative accuracy score uses EV maximization, which is an alternative-based decision rule, as a criterion for accuracy.

The result of the greatest interest, however, is that the relationship between processing and accuracy changes sign for those decision problems involving both time pressure and high variance in the probabilities. Note that it is exactly the combination of high time pressure and high variance in probabilities where the Monte-Carlo simulation indicated that attribute-based forms of processing, e.g., the EBA strategy and lexicographic rule, were better than either one of the alternative-based strategies, i.e., the weighted additive or equalweight additive rules (See Table 3, Dominance Yes, Variance High, Time Pressure Severe). In other words, a person striving to maintain accuracy in a severely time pressured, high variance decision environment should, according to the simulation results, utilize more attribute-based processing. Our results show that the use of relatively more attribute-based processing led to better relative accuracy for exactly those time pressured, high variance decision problems (a negative correlation implies that lower values for PATTERN, signifying more attribute-based processing, are associated with higher relative accuracy).

Insert Table 7 about here

Discussion

The central result from Study 2 is that people exhibit a surprising degree of adaptivity in their decision behavior. Decision processes were sensitive to a context variable that influences the relative accuracy of heuristics, without impacting on relative effort. Decision processes were also sensitive to the important task variable of time pressure. These findings of adaptivity are particularly strong in that they were exhibited by the same subjects on different trials. Moreover, there was a relationship between processing strategy and the relative accuracy of choice as a function of changes in the task environment. Finally, the general pattern of adaptive behavior was in a direction consistent with the simulation results.

The results dealing with time pressure and decision processes were also of interest. Support was found for the hypotheses that increased time pressure would result in (1) acceleration of information processing, (2) filtration of information to be processed, and (3) changes in the choice heuristics used to make a decision. As noted earlier, prior research has supported the acceleration and filtration hypotheses. The present study is the first to demonstrate clear changes in choice processing strategies as a function of time pressure.

The fact that there appear to be at least three ways in which people can adapt to time pressure leads to the following question: Is there an ordering to the adaptive strategies people use to deal with time pressures? That is, do people first try to deal with time constraints through acceleration and perhaps filtration of processing? Selecting an alternative decision process in response to time pressure may only occur if the first two responses are not adequate. The purpose of the third study is to investigate that possibility by examining a case of less severe time pressure

Study 3: Effects of Moderate Time Pressure on Choice

This study examines the extent and direction of adaptive decision processing when the amount of time pressure is less severe than that investigated in Study 2. This study also examines the effects of the context variable dealing with the variance in probabilities.

Method

Subjects. Ten undergraduates at Duke University served as subjects. Subjects participated in return for course credit and the chance to win up to $9.99.

Stimuli and Procedures. The stimuli and procedures used in this experiment were the same as those used in Study 2. The only difference was that the amount of time available in those decision problems with a time constraint was increased to 25 seconds, as opposed to the 15 seconds used in Study 2.

Results

The measures of process and accuracy used in this study were the same as those in Study 2. A summary of both the process and accuracy results for Study 3 can be found in Table 8.

The results for Study 3 parallel those for Study 2 with respect to items of information acquired (ACQ) and BOXTIME. There is a main effect of time pressure for each, with fewer items of information acquired ($M = 37.3$ vs. $M = 23.2$, $F = 118.6$, $p < .01$) and less time spent ($M = 26.2$ vs. $M = 12.8$, $F = 124.8$, $p < .01$) under greater time pressure.[8]

The results also support acceleration, in that there is a main effect of time pressure on time per acquisition (TPERACQ). People process information more quickly under time pressure ($M = .65$ vs. $M = .56$, $F = 71.48$, $p < .01$).

There is some evidence for filtration, although weaker than in Study 2. There is a marginal main effect of time pressure on proportion of time spent on the most likely outcome (PTMI), with this proportion greater under time pressure ($M = .31$ vs. $M = .33$, $F = 3.36$, $p = .067$). There is no effect of time pressure on the proportion of time spent on probability information, however.

Finally, there is very little evidence of time pressure effects on the pattern of processing. There is no main effect on the PATTERN measure ($F = .03$, n.s.) or variance in the proportion of time spent on the various attributes ($F = 1.89$, n.s.). There is a marginal effect of time pressure on the proportion of time spent on the various alternatives (VAR-ALTER), with greater variance under lower time pressure, opposite to the predicted effect ($M = .25$ vs. $M = .22$, $p = .069$). Hence, unlike the results for Study 2, there is no evidence in Study 3 that a shift in processing strategies occurred under time pressure. This conclusion is reinforced when the correlations between the relative amount of alternative-based processing (PATTERN) and relative accuracy are examined across the various time pressure, block, and variance conditions.[9] As shown in the last row of Table 8, the correlations are all positive, showing that more alternative-based processing is consistently associated with greater relative accuracy. This contrasts to the shift in the sign of the correlations found in Study 2.

The overall results for the relative accuracy measure also show no main effect for time pressure ($F = .42$, n.s.). However, there is a significant time pressure by block interaction, again showing that accuracy was only low in the first block under time pressure ($F = 5.05$, $p < .05$).

Although the results for adaptivity of strategy to time pressure are not significant, the context variable had similar effects to those of Study 2. There were main effects of context on acquisitions (ACQ) ($F = 14.35$, $p < .01$) and boxtime ($F = 13.47$, $p < .01$) , with lower values in the high variance conditions. There were also effects of context on the process variables. The predominant pattern of processing becomes more attribute-based ($M = .12$ vs. $M = -.13$, $F = 45.01$, $p < .01$); there is a greater variance in the proportion of time spent on the various alternatives (VAR-ALTER) ($M = .20$ vs. $M = .27$, $F = 10.49$, $p < .01$); and there is greater variance in the proportion of time spent on the various attributes (VAR-ATTRIB) ($M = .20$ vs. $M = .34$, $F = 14.25$, $p < .01$) for the greater variance condition. These results are important, for they show that the subjects in the experiment <u>did</u> show adaptivity to the variance manipulation by changing strategies. Hence, the failure to show such an effect for time pressure is not due to a total failure to obtain adaptivity.[10]

To summarize, the results for the no time pressure problems versus decision problems involving a time pressure of 25 seconds indicated strong evidence of acceleration of processing, marginally significant evidence for filtration of information to be processed, and no evidence of changes in decision heuristics. A comparison of the results for Study 3 with those of Study 2 suggests the hypothesis that people adapt to time pressure in a ordered sequence of ways. First, they try to speed up their rate of processing. Next they will selectively process information. Finally, they will select a different decision or evaluation strategy.

The effects of the context variable replicate those reported for Study 2, and support the conclusion that people will adapt decision processes to changes in the decision environment that impact the relative accuracy of heuristics without affecting the relative effort.

General Discussion

Past research has shown that the same individual will often employ diverse strategies in making a decision, contingent on task demands (Payne, 1982). The use of multiple decision strategies extends to children, as well as adults (Klayman, 1985). Similarly, a growing amount of evidence from the study of human performance in several other cognitive tasks indicates that an individual may use many different cognitive processes (strategies) to reason and solve problems (Reder, 1982; Siegler, 1986).

As Siegler (1986) has argued, "children (and adults) have good reasons to use multiple strategies. Strategies differ in their accuracy, in how long they take to execute, in their demands on processing resources, and in the range of problems to which they apply (p. 1)". A major problem for current cognitive research is to be able to better understand and predict when a particular strategy will be employed.

This paper has examined the role of effort and accuracy considerations in the selection of information processing strategies for making a choice.

The general hypothesis is that the selection among strategies is adaptive, in the sense that a decision maker will choose strategies that are relatively efficient in terms of effort and accuracy as task and context demands are varied. The first part of the paper outlined an approach to modelling the inpact of task and context variables on decision strategies. The approach is based on the use of elementary information processes to measure effort and use of computer simulation models to examine accuracy and effort tradeoffs. Study 1 used Monte-Carlo simulation techniques to examine the impact of variations in several aspects of the choice environment, including the presence or absence of time pressure, variance in weights, presence or absence of dominated alternatives, and different problem sizes, on the accuracy and effort of a variety of choice heuristics. This simulation identified strategies which approximate the accuracy of normative procedures while requiring substantially less effort. However, no single heuristic did well across all task and context conditions. A decision maker striving to maintain a high level of accuracy with a minimum of effort would have to adaptively choose from a repertoire of heuristics. Of particular interest was the finding that under time constraints, several attribute-based heuristics (e.g., Elimination-by-aspects) were clearly superior in terms of accuracy to a normative procedure such as expected value maximization.

Studies 2 and 3 directly tested the degree of correspondence between the efficient strategies for a given decision problem identified by the simulations and the actual information processing strategies people use to make a choice. People were shown to be highly adaptive in their responses to changes in the nature of the alternatives available to them, and to the presence or absence of time pressure. The results for actual decision behavior tended to validate the models of decision strategies and the simulation estimates of accuracy and effort in various choice environments.

More specifically, subjects were shown to use several approaches in adapting to different decision environments. Subjects acquired less information, spent less time overall and less time per acquisition, used more attribute-based processing, and displayed greater variance in the proportion of time spent on the various alternatives and attributes in situations where the context variable of variance in the weights (probabilities) was high rather than low. Such adaptivity in strategy usage in response to a context variable demonstrates that people are sensitive to a change in the task environment that impacts on the relative accuracy of heuristics without affecting relative effort.

In addition, several effects of time pressure were demonstrated. Under moderate time pressure, subjects were shown to accelerate their processing and, to a lesser extent, to focus on a subset of the available information. Under severe time pressure, people accelerated their processing, focused on a subset of the information, and changed their decision strategies. There was slightly more attribute-based processing and more variance in the proportion of time spent on various attributes as time pressure increased. In addition, these changes appeared to be appropriate in terms of accuracy, as more attribute-based processing was associated with higher gains in high time pressure, high variance in weights environments. Also interesting is the fact that the adaptive use of heuristics was greater for the second block of decision problems. This suggests that people may learn appropriate heuristics to use with experience in solving certain types of decision problems.

There are several important aspects of the time pressure results. First, they provide one of the clearest demonstrations in the literature to date of adaptivity of processing strategies to time pressure. Second, the results of Studies 2 and 3, taken together, imply that there may be a hierarchy of responses to time pressure. People may first attempt to simply accelerate, or speed up their processing. That is, they may first try to do the same things faster. If the time pressure is too great for acceleration to suffice, individuals may next engage in filtration, focusing on a subset of the available information. Finally, people may change strategies when time pressures become extreme. The evidence also suggests that such strategy changes are in the appropriate direction in terms of preserving accuracy while minimizing effort.

Taken as a whole, the results provide very strong evidence for adaptivity in decision making. Individuals change strategies from one choice problem to the next depending upon the structure of the choice environment for each problem. The current studies are the only ones of which we are aware which provide such extensive within-individual evidence of adaptivity. This variability in approach from one problem to the next implies that humans possess abilities for assessing choice environment properties; characterizing such abilities would be a fruitful area for study.

The results also provide impressive validation for the conceptual and simulation approaches outlined in Johnson and Payne (1985). Subjects not only change strategies in response to changes in choice environments, but they appear to change in directions predicted by the simulation. This implies that such simulations may be useful in understanding adaptive responses to other aspects of choice environments, such as the intercorrelation structure of the attributes (Johnson, Meyer, & Goshe, 1986). However, certain environmental properties may be more easily noticed, and hence more adapted to, then others.

The evidence for adaptive use of heuristics obtained in this study suggests a picture of the human decision maker that is fairly optimistic in terms of rational behavior. People clearly do use choice heuristics that may lead to violations of certain principles of rationality (Tversky, 1969). The use of heuristics may reflect a tradeoff of effort and accuracy, or reflect the fact that the decision maker has no other choice in some decision environments than the use of a heuristic (Simon, 1981). However, our results suggest that people can adaptively select from a repertoire of processing strategies. That is, people use heuristics that are often appropriate given task and context factors.

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Footnotes

[1]EIP's can also be used as components in production system models of decision strategies. Productions are (condition) --> (action) pairs, where the action is performed only if the condition is matched. EIP's could be used as the actions, and the results of earlier actions could be used as parts of conditions (e.g., if A and B have been read, then add A and B).

[2]To provide insight into the ranges of values possible, the average number of EIP's required for the weighted additive rule to run to completion ranged from 28 for the two alternative, two attribute case to 400 for the eight alternative, eight attribute case. Comparable figures for the lexicographic strategy are 21.3 (2 x 2) and 172.5 (8 x 8).

[3]The standard error for the effort values in Table 2 is ± 2.75, and for the accuracy values in Tables 2 and 3 it is $\pm .029$, $p < .05$.

[4]Subjects took about 50 seconds, on average, when under no time pressure in the pilot studies. Those pilot studies revealed that 15 seconds represented substantial time pressure for the subjects.

[5]In addition, one could have same alternative, same attribute transitions (reacquisitions) or different alternative, different attribute transitions. These two cases are not particularly germane to our major hypotheses, however.

[6]The degrees of freedom for all of the F-values reported for this study are 1 and 617.

[7]The cell-sizes for the correlations in Table 7 ranged from 64 to 96.

[8]For all F-values reported for Study 3, the degrees of freedom are 1 and 400.

[9]The cell-sizes for these correlations ranged from 40 to 60.

[10]Although there were other significant results that paralleled those of Study 2, they are not reported in detail here. These were effects of block on BOXTIME ($F = 34.2$, $p < .01$), ACQ ($F = 21.86$, $p < .01$), time per acquisition ($F = 20.71$, $p < .01$), and PTMI ($F = 5.66$, $p < .05$). There were block by time pressure interactions for BOXTIME ($F = 22.82$, $p < .01$), ACQ ($F = 11.18$, $p < .01$), and time per acquisition ($F = 11.69$, $p < .01$). Finally, there were time pressure by variance interactions for BOXTIME ($F = 8.47$, $p < .01$) and ACQ ($F = 7.58$, $p < .01$).

Table 1

Elementary Information Processing Operations (EIPs) used by Johnson and Payne (1985)

READ	Read an alternative's value on an attribute into STM
COMPARE	Compare two alternatives on an attribute
DIFFERENCE	Calculate the size of the difference of two alternatives for an attribute
ADD	Add the values of an attribute in STM
PRODUCT	Weight one value by another (multiply)
ELIMINATE	Remove an alternative from consideration
MOVE	Go to next element of external environment
CHOOSE	Announce preferred alternative and stop process

Table 2

Simulation Results for Accuracy and Effort of Heuristics in the No Time Pressure Decision Problems

		Task Environments			
Decision Strategy	Dominance Possible:	Yes		No	
	Variance in Probs:	Low	High	Low	High
WADD		1.0[1]	1.0	1.0	1.0
		(160)[2]	(160)	(160)	(160)
EQW		.89	.67	.41	.27
		(85)	(85)	(85)	(85)
LEX		.69	.90	.67	.90
		(60)	(60)	(60)	(60)
LEXSEMI		.71	.87	.64	.77
		(79)	(78)	(79)	(81)
EBA		.67	.66	.54	.56
		(87)	(88)	(82)	(82)
MCD		.62	.48	.07	.09
		(148)	(148)	(141)	(140)
SAT		.32	.31	.03	.07
		(49)	(49)	(61)	(61)
EBA+ADD		.84	.79	.69	.66
		(104)	(106)	(102)	(102)
EBA+MCD		.69	.59	.29	.31
		(89)	(89)	(86)	(86)
RAND		0	0	0	0

[1]Relative Accuracy.

[2]Unweighted operations count.

Table 3

Simulation Results for Accuracy of Heuristics under Time Pressure

		Task Environments											
	Dominance Possible:	YES						NO					
Decision	Variance in Probs:	LOW			HIGH			LOW			HIGH		
Strategy	Time Pressure	Low	Mod.	Sev.	Low	Mod.	Sev.	Low	Mod.	Sev.	Low	Mod.	Sev.
WADD		.91[1]	.80	.28	.91	.80	.28	.90	.77	.12	.92	.82	.24
EQW		.88	.82	.72	.66	.65	.55	.41	.34	.26	.24	.25	.18
LEX		.70	.69	.47	.90	.90	.59	.69	.68	.48	.90	.90	.60
LEXSEMI		.71	.66	.40	.87	.83	.49	.63	.59	.43	.76	.75	.51
EBA		.70	.68	.49	.76	.73	.65	.63	.60	.48	.67	.67	.61
MCD		.58	.49	.23	.44	.35	.17	.03	-.01	-.02	.04	.03	.02
SAT		.38	.34	.30	.32	.34	.23	.03	.04	.06	.07	.05	.04
EBA+ADD		.86	.79	.43	.86	.82	.48	.73	.66	.27	.75	.74	.43
EBA+MCD		.74	.65	.44	.67	.60	.49	.35	.32	.27	.40	.41	.36
RAND		0	0	0	0	0	0	0	0	0	0	0	0

[1]Accuracy is measured relative to the performance of the WADD rule in the no time pressure condition.

Table 4

Sample of Stimulus Sets Used in Study 2

LOW VARIANCE SETS						HIGH VARIANCE SETS					
Set 1:	Probs:	.22	.26	.24	.28	Set 1:	Probs:	.03	.02	.09	.86
G1:	Amts:	8.73	7.83	1.74	8.91	G1:	Amts:	5.41	8.39	7.43	7.76
G2:	Amts:	7.54	4.64	5.11	6.73	G2:	Amts:	8.99	7.29	2.05	7.78
G3:	Amts:	5.37	5.41	6.03	3.55	G3:	Amts:	1.48	3.53	1.79	7.06
G4:	Amts:	5.07	7.51	5.12	2.50	G4:	Amts:	1.21	2.09	0.81	7.88
Set 5:	Probs:	.20	.31	.20	.29	Set 5:	Probs:	.20	.04	.07	.69
G1:	Amts:	4.39	5.59	3.20	9.90	G1:	Amts:	6.86	1.18	4.96	0.84
G2:	Amts:	8.33	3.40	3.29	6.99	G2:	Amts:	1.38	3.34	8.49	2.91
G3:	Amts:	5.50	7.10	0.28	9.07	G3:	Amts:	8.04	1.07	0.54	6.85
G4:	Amts:	3.67	3.10	2.29	6.56	G4:	Amts:	1.00	0.72	0.71	8.47
Set 9:	Probs:	.27	.15	.31	.27	Set 9:	Probs:	.02	.56	.01	.41
G1:	Amts:	7.21	9.83	4.00	7.18	G1:	Amts:	1.89	6.77	2.92	5.62
G2:	Amts:	1.36	1.64	0.87	2.38	G2:	Amts:	4.31	2.77	7.13	2.46
G3:	Amts:	1.06	1.58	9.77	9.70	G3:	Amts:	3.24	8.10	4.94	1.83
G4:	Amts:	3.52	5.96	8.27	9.85	G4:	Amts:	9.07	7.00	1.00	4.21

Table 5

Process Measures as a Function of Time Pressure, Context, and Decision Block

Time Pressure:	No Time Pressure				15 sec			
Variance:	LOW		HIGH		LOW		HIGH	
Block:	1st	2nd	1st	2nd	1st	2nd	1st	2nd
ACQ	46.6	35.3	35.1	27.6	18.3	17.6	15.6	15.4
BOXTIME	37.2	25.0	23.9	18.0	8.7	8.4	7.8	7.4
TPERACQ	.754	.668	.650	.622	.492	.487	.507	.493
PTMI	.322	.335	.419	.417	.347	.352	.446	.480
PTPROB	.232	.252	.245	.285	.283	.297	.281	.289
PATTERN	-.111	-.107	-.319	-.329	-.103	-.164	-.446	-.408
VAR-ALTER	.015	.015	.018	.022	.020	.015	.020	.019
VAR-ATTRIB	.181	.200	.343	.559	.210	.281	.495	.534

ACQ = Number of information boxes examined.

BOXTIME = Average time spent examining information boxes.

TPERACQ = Time per information acquisition.

PTMI = Proportion of time on the most important attribute.

PTPROB = Proportion of time on the probability information.

PATTERN = Index reflecting relative amount of attribute-based (-) and alternative-based (+) processing.

VAR-ALTER = Variance in the proportion of time spent on each alternative.

VAR-ATTRIB = Variance in the proportion of time spent on each attribute (including both payoff and probability information).

Table 6

Mean Relative Accuracy as a Function of Time Pressure, Context, and Decision Order

Time Pressure:	No Time Pressure			15 seconds		
Variance:	LOW	HIGH	MEAN	LOW	HIGH	MEAN
Relative Accuracy (1st half)	.694	.585	.628	.269	.398	.333
Relative Accuracy (2nd half)	.609	.611	.610	.616	.643	.629
Relative Accuracy (Total)	.643	.595		.442	.520	
	MEAN = .619			MEAN = .481		

Table 7

Correlation between Pattern of Processing and Relative Accuracy as a Function of Time Pressure, Context, and Decision Block

Time Pressure:	No Time Pressure		15 Seconds	
Variance:	LOW	HIGH	LOW	HIGH
Decision Order				
1st half	.10	.06	.20	.10
2nd half	.41*	.30*	.31*	-.20(.08)

*Significant, $p < .05$.

Table 8

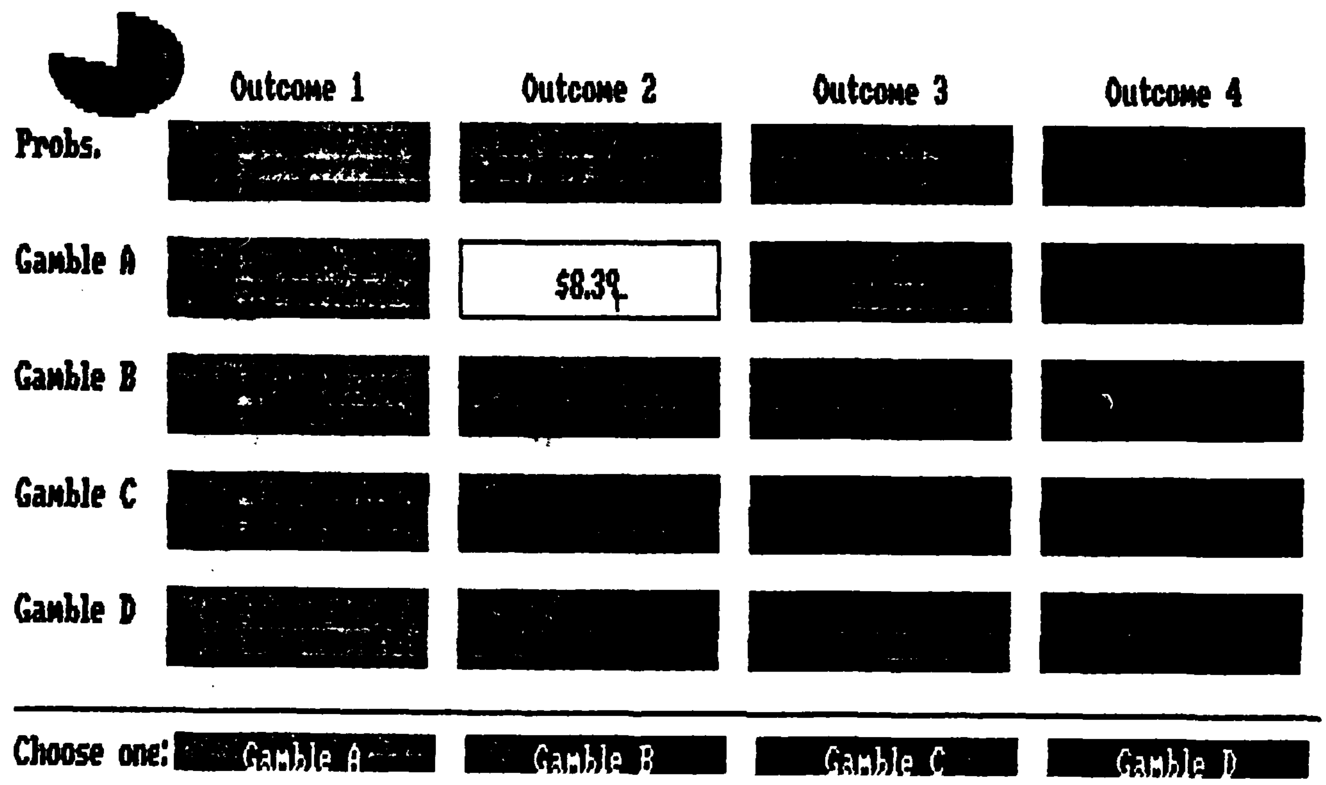
Summary of Process and Accuracy Results for Study 3

Time Pressure:		No Time Pressure				25 Sec.			
	Variance:	LOW		HIGH		LOW		HIGH	
Process	Decision Block:	1st	2nd	1st	2nd	1st	2nd	1st	2nd
ACQ		45.3	36.6	38.5	27.6	24.9	22.9	23.3	21.9
BOXTIME		37.9	22.9	27.9	16.9	13.9	12.6	13.0	11.6
TPERACQ		.768	.643	.724	.607	.567	.559	.565	.538
PTMI		.283	.282	.325	.351	.260	.322	.361	.384
PTPROB		.235	.214	.251	.253	.233	.237	.244	.238
PATTERN		.089	.135	-.136	-.079	.087	.175	-.148	-.133
VAR-ALTER		.011	.013	.017	.018	.012	.013	.013	.016
VAR-ATTRIB		.205	.198	.253	.338	.187	.225	.342	.445
Accuracy									
Relative Accuracy		.541	.474	.508	.450	.381	.664	.252	.490
Correlation Of Relative Accuracy & Pattern		.18	.49*	.12	.29	.30*	.42*	.09	.33*

* $p < .05$

Figure Caption

Figure 1. Example of stimulus display with time pressure clock.


Outcome 1
Outcome 2
Outcome 3
Outcome 4
Probs.
Gamble A
$8.39
Gamble B
Gamble C
Gamble D
Choose one:
Gamble A
Gamble B
Gamble C
Gamble D

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