Adaptive Strategy Selection in Decision Making

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The role of effort and accuracy in the adaptive use of decision processes is examined. A computer simulation using the concept of elementary information processes identified heuristic choice strategies that approximate the accuracy of normative procedures while saving substantial 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 more accurate than a truncated normative procedure. Using a process-tracing technique that monitors information acquisition behaviors, two experiments tested how closely the efficient processing patterns for a given decision problem identified by the simulation correspond to the actual processing behavior exhibited by subjects. People appear highly adaptive in responding to changes in the structure of the available alternatives and to the presence of time pressure. In general, actual behavior corresponded to the general patterns of efficient processing identified by the simulation. Finally, learning of effort and accuracy trade-offs are discussed.

A major empirical finding of recent decision research is that individuals use a variety of choice strategies (Abelson & Levi, 1985). Sometimes a person will use a compensatory strategy that processes all relevant information and trades off the good and bad aspects of each alternative. At other times, the same person might use a noncompensatory decision strategy, which avoids trade-offs among values and typically reduces information processing demands by ignoring potentially relevant problem information. For example, the lexicographic strategy simply selects the alternative that is best on the most important attribute if there are no ties. The use of a particular decision strategy is contingent on many task and context variables (Payne, 1982), such as the number of alternatives.

Evidence of contingent information processing in decisions raises an important question: Why are certain decision strategies applied to certain decision problems? One general perspective looks at strategy selection as a function of both costs, primarily the effort required to use a rule, and benefits, primarily the ability of a strategy to select the best alternative (Beach & Mitchell, 1978; Russo & Dosher, 1983). A cost–benefit approach to strategy selection maintains the concept of calculated rationality (March, 1978) by including the costs of executing the decision process in the assessment of rationality. Furthermore, because the costs and benefits of various decision strategies vary across different problems, the cost–benefit perspective provides the potential for explaining why decision strategies vary across situations.

This article examines the adaptive selection of choice strategies and is structured as follows: First, a framework for measuring both the cognitive effort and accuracy of different strategies in various decision environments is presented. That framework decomposes choice strategies into a common set of more elementary information processes (EIPs). Next, a Monte-Carlo simulation of the effort and accuracy of choice strategies in a variety of choice environments is reported and the impact of time constraints on the relative accuracy of decision strategies is examined. The simulation identifies general *patterns* of adaptivity in processing that might be expected if the effort and accuracy framework is correct and is used to hypothesize patterns of context and task effects for a particular decision environment. Two experimental studies are then reported that examine the correspondence between the patterns identified by the simulation and actual behavior.

Effort and Accuracy in Choice

One major difficulty in using a cost–benefit perspective to examine strategy selection has been the lack of an easily calculated and conceptually appropriate measure of effort. A second area of concern has been the lack of agreement on how to measure choice accuracy.

Measuring Strategy Effort

Building on ideas of Newell and Simon (1972), Johnson and Payne (1985) suggested that decision strategies can be decomposed into EIPs. A decision strategy can then be seen as a sequence of events, such as reading the values of two alternatives on an attribute, comparing them, and so forth.

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One set of EIPs for decision making follows: (a) *read* an alternative's value on an attribute into short-term memory (STM), (b) *compare* two alternatives on an attribute, (c) *add* the values of two attributes in STM, (d) calculate the size of the *difference* of two alternatives for an attribute, (e) weight one value by another (*product*), (f) *eliminate* an alternative from consideration, (g) *move* to next element of the external environment, and, (h) *choose* the preferred alternative and end the process. Such EIPs provide a common language for describing seemingly diverse decision strategies in terms of their underlying components. 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 versus nonanalytic (Beach & Mitchell, 1978) or analytic versus intuitive (Hammond, 1986). The EIPs can also be used as components in production system models of decision strategies (see Johnson & Payne, 1985, for an example). Productions are *condition* → *action* pairs, where the action is performed only if the condition is matched. The EIPs 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).

A particular set of EIPs represents a theoretical judgment regarding the appropriate level of decomposition for decision processes. For instance, the product operator might itself be decomposed into more elementary processes. We hypothesize, however, that a reasonable approximation of the cognitive effort associated with a strategy may be obtained from the foregoing level of decomposition.

A count of the total number of EIPs used by a given strategy to reach a decision in a particular choice environment provides a measure of the effort associated with the use of that decision strategy in that environment (O. Huber, 1980; Johnson, 1979). A number of studies of cognition use EIP counts to measure processing load (e.g., Card, Moran, & Newell, 1983). A study that directly relates EIP counts to measures of decision effort is described in Bettman, Johnson, and Payne (1987).

Measuring Accuracy

Accuracy of choice can be defined in many ways. Quality of choice can be defined by basic principles of coherence such as not selecting dominated alternatives or not displaying intransitive patterns of preferences. Note that violations of dominance can be defined in terms of a single choice, whereas violations of transitivity are defined over several choices. More specific criteria for decision quality can be developed in certain types of choice environments. For instance, the expected utility (EU) model is often suggested as a normative decision procedure for risky choice because it can be derived from more basic principles. A special case of the EU model, the maximization of expected value (EV), has been used as a criterion to investigate the accuracy of decision heuristics via computer simulation (Thorngate, 1980; Johnson & Payne, 1985). The main advantage of EV as an accuracy measure is that utility values from individual decision makers are not required to operationalize the rule. A similar model, the compensatory weighted additive rule, is often used as a criterion for decision effectiveness in multiattribute choice (Zakay & Wooler, 1984).

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

This study provides predictions about the patterns of processing that would be exhibited in various task environments by an *idealized* adaptive decision maker attending to both effort and accuracy in selecting a decision strategy. The simulation was used to generate hypotheses about the types of processing that might occur in the experiments described below if decision makers adapt to different task environments as predicted by the proposed framework.

The simulation extends prior work reported in Johnson and Payne's (1985) article. In particular, the present study investigates environments with time constraints, potentially one of the most significant task variables. Under time constraints, heuristics might be even more accurate than a "normative" strategy such as maximization of expected value, because the heuristic's accuracy may degrade under increasing time pressure at a slower rate than a more comprehensive processing rule (e.g., EV) degrades. One reason for this is that heuristics require fewer operations and will generally be "further along" when time runs out. Furthermore, people may use heuristics under time pressure 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. Deciding how to choose then becomes a selection of the "best" of the available heuristics, not a choice between using some heuristic or the more normative rule.

Choice Environment and Processing Characteristics

The decision task used in the simulation study and in the empirical studies was a special type of risky choice, with alternatives with outcomes that have different payoffs but the same probability for each alternative. In other words, each of the alternatives may have a different value for a given outcome, but the probability of receiving that outcome is the same for all the alternatives. This allows the decision task to be interpreted as either a riskless choice or as a form of risky choice (Keeney & Raiffa, 1976). In the riskless interpretations, the probabilities function as attribute weights that apply across alternatives. One can look at a probability of .20, for example, as the weight given to a particular attribute across all alternatives. Note that a statement about structural similarity is all that is being claimed; the empirical work described later used the risky choice interpretation.

In solving risky choice problems, the decision maker must search among probabilities and the values associated with the outcomes for each alternative. Different decision strategies can be thought of as different rules for conducting that search and vary in a number of aspects (see Bettman, 1979). One of the most important distinctions among rules is the extent of compensatory as compared to noncompensatory processing.

A related aspect is the degree to which the amount of processing is consistent (or selective) across alternatives or attributes. That is, is the same amount of information examined for each alternative or attribute, or does the amount vary? In general, it has been assumed that more consistent processing across alternatives is indicative of a more compensatory decision strategy (Payne, 1976). Consistent processing sometimes involves examination of all information for every alternative and attribute. A more variable (selective) processing pattern, on the other hand, is seen as indicating a strategy of eliminating alternatives on the basis of only a partial processing of information, without considering whether additional information might compensate for a poor value.

Another general processing characteristic is the total amount of processing carried out. Whether processing is consistent or not, the total amount of information examined can vary, from quite cursory to exhaustive.

A final aspect of processing concerns whether the search and evaluation of alternatives proceeds across or within attributes or dimensions. The former is often called wholistic or *alternative*-based processing and the latter dimensional or *attribute*-based processing. In alternative-based processing, multiple attributes of a single alternative are considered before information about a second alternative is processed. In contrast, in attribute-based processing, the values of several alternatives on a single attribute are processed before information about a second attribute is processed. Russo and Dosher (1983) suggest that attribute-based processing is cognitively easier.

The next section provides additional detail on the specific strategies used in the simulation. Following these descriptions, we provide examples of how the specific strategies exemplify the above distinctions.

Decision Strategies Examined

The simulation investigated 10 decision strategies. The 10 strategies were selected because they vary substantially in the amount of information used and in the way that available information is used to make a choice.

The most information intensive strategy examined was a version of a *weighted additive* (WADD) compensatory process, which can be thought of as a version of expected value maximization. The strategy considers the values of each alternative on all of the relevant attributes (outcomes) and all of 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 (probability) by the value and sums over all attributes to arrive at an overall evaluation of an alternative. The rule selects the alternative with the highest evaluation. The *random* (RAN) choice rule, in contrast, chooses an alternative at random with no search of the available information, providing a minimum baseline for measuring both accuracy and effort.

In addition to these two baseline rules, six choice heuristics and two combination strategies were implemented. The *equal weight* (EQW) rule examines all alternatives and all attribute values for each alternative. However, the rule ignores information about the relative importance (probability) of each attribute. In some contexts, the equal weight rule has been advocated as a highly accurate simplification of the risky choice process (Thorngate, 1980). *Elimination by aspects* (EBA) (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. The process continues with the second most important attribute, then the third, and so on, until one alternative remains.

The *majority of confirming dimensions* (MCD) rule (Russo & Dosher, 1983) involves processing pairs of alternatives. The values for each of the two alternatives are compared on each attribute, and the alternative with a majority of winning (better) attribute values is selected. In the case of an equal number of winning values for the two alternatives, our version of this rule retained the alternative winning the comparison on the last attribute. The retained alternative is then compared to the next alternative among the set of alternatives. The process of pair-wise comparison repeats until all alternatives have been evaluated and the final winning alternative identified. The *satisficing* (SAT) rule (Simon, 1955) considers alternatives one at a time, in the order they occur in the set. Each attribute of an alternative is compared to a cutoff value. If any attribute value is below the cutoff value, that alternative is rejected. The first alternative which passes the cutoffs for all attributes is chosen, so a choice can be made before all alternatives have been evaluated. In the case where no alternative passes all the cutoffs, a random choice is made.

Two versions of the lexicographic choice rule were implemented. For the strict *lexicographic* (LEX) rule, the most important attribute is determined, the values of all the alternatives on that attribute are examined, and the alternative with the best 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. Because the simulation generates attributes as continuous random variates, ties almost never occur. A *lexicographic semi-order* (LEXSEMI) rule (Tversky, 1969) was also examined. 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 of the best alternative on the most important attribute, they are considered to be tied. The potential advantage of the LEXSEMI rule is that it ensures that an option that 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+WADD) rule. This rule used an EBA process until the number of available alternatives remaining was three or fewer, and then used a weighted additive rule to select among the remaining alternatives. The other combined strategy, *elimination-by-aspects plus majority of confirming dimensions* (EBA+MCD), used an elimination-by-aspects process to reduce the problem size, and then used a majority of confirming dimensions heuristic to select from the reduced set. These combinations were used because they had been observed in several previous choice process studies (e.g., Bettman & Park, 1980).

As noted earlier, these choice strategies differ on a number of aspects, such as the degree to which the amount of processing is consistent or variable across attributes or alternatives, the pattern of processing (alternative based or attribute based), and the total amount of processing. The various strategies represent different combinations of these aspects. The weighted adding strategy uses consistent and alternative-based processing and examines all available information. The equal weight strategy uses consistent and alternative-based processing but uses a subset of the available information. The MCD rule is consistent, attribute-based, and ignores weight information. The EBA rule implies a variable (selective) pattern of processing that is attribute based. The total amount of information processed by EBA depends on the particular values of the alternatives and cutoffs. The lexicographic strategies are also selective and attribute based, and the satisficing strategy is selective and alternative based. The total amount of information processed is also contingent upon the particular values of the alternatives for these strategies.

The simulation provides insights into how aspects of processing, as exemplified by individual strategies, might change across different choice environments if adaptivity is exhibited. Other aspects of processing, such as the proportion of processing devoted to the probabilities and the proportion of processing devoted to the most probable (important) attribute, will also be considered.

Task and Context Variables

Three task variables were examined. The number of alternatives and number of attributes were each varied at three levels (2, 5, and 8) in order to manipulate task complexity. The third task variable included was time pressure, varied at four levels. One level involved no time pressure, with each rule using as many operations as needed. The three other levels of time constraint were a maximum of (a) 50 EIPs (severe time pressure), (b) 100 EIPs (moderate pressure), and (c) 150 EIPs (low pressure). These time (EIP) constraint values were selected on the basis of an analysis of the maximum number of EIPs associated with the most effortful rule (weighted additive).[1] Note that the total number of EIPs was used to operationalize time pressure. This implicitly assumes that each EIP takes a similar amount of time. The sensitivity of the analyses to this assumption is examined later.

A key issue in dealing with the time constraints is how rules should select among alternatives if they run out of time. Several rules identify one alternative as the best seen so far (i.e., the WADD, EQW, and MCD rules) and select that alternative when they run out of time. The EBA, LEX, and SAT rules all pick an option randomly from those alternatives not yet eliminated. Because the EBA and lexicographic rules were able to process all alternatives on at least one attribute, even for the largest problem size under the most severe time constraint, the choice came from the set already processed but not eliminated. For the SAT rule in this most severe case, if the first alternative was not acceptable, then random choice among the remaining alternatives seemed to be the most reasonable option. 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.

Finally, two context variables were included. Context variables, unlike task variables, are associated with the particular choice object values (Payne, 1982). One context variable was the presence or absence of dominated alternatives. Removing dominated alternatives produces efficient choice sets. McClelland (1978) suggested that the success of the equal weighting simplification strategy is dependent on the presence of dominated alternatives. Empirical evidence showing that dominated alternatives can impact choice was provided by J. Huber, Payne, and Puto (1982). This implies that dominated alternatives are not simply disregarded.

The second context variable was the degree of dispersion of probabilities within each gamble. To illustrate, a four-outcome gamble with a low degree of dispersion might have probabilities of .30, .20, .22, and .28 for the four outcomes, respectively. On the other hand, a gamble with a high degree of dispersion might have probabilities such as .68, .12, .05, and .15 for the four outcomes. This variable was chosen because Thorngate (1980) had suggested that probability information may be relatively unimportant in making accurate risky choices (see also Beach, 1983). Obviously, if all of the outcome probabilities were identical, probability information would not matter. On the other hand, if one outcome is certain, then examining the probability information to find that outcome is crucial. What is unclear is how sensitive heuristics are to the dispersion in probabilities, and how adaptive actual behavior is to such a context variable. We therefore examined decision sets with either low or high dispersion.

JNDs and Cutoff Values

Three of the rules, EBA, SAT, and LEXSEMI, involve parameters that affect the potential effort and accuracy of the rules. For EBA and SAT this is the cutoff value used to eliminate alternatives. For the LEXSEMI rule, it is the value of the JND. Although these parameters are, in some sense, under the control of the decision maker for each decision, we wanted to establish a priori values that would be the same for all decisions made by the simulation. A pilot simulation without any time constraints was run to identify the best levels, with all attributes in the simulation drawn from a uniform distribution bounded by 0 and 1,000. We manipulated both cutoffs (100, 300, and 500) and JNDs (1, 50, and 100) and selected values that represented the most efficient accuracy–effort trade-offs averaged across the entire set of decisions. We found that values of the cutoff of 500 and 300 were most efficient for EBA and SAT, respectively, and that a JND of 50 gave the best performance for the LEXSEMI rule. The results presented

[1] To provide insight into the ranges of values possible, the average number of EIPs 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 × 2) and 172.5 (8 × 8).

for the EBA, SAT, and LEXSEMI rules are for the most efficient values for each rule.

Method

Each of the 10 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 dispersion of probabilities or weights) by 2 (presence or absence of 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.

Results

Effort was measured using EIPs, and accuracy was measured using EV (WADD) maximization. Specifically, effort was measured by the total count of the EIPs used by a specific decision rule to make a selection from a particular set of alternatives. This measure assumes that each EIP requires the same level of time or mental effort. Later, we report results that relax that assumption.

The EV-based measure of accuracy compared the relative performance of strategies to the two baseline strategies: (a) the maximization of expected value (WADD), and (b) random choice. The measure was defined by the following equation:

$$\text{relative accuracy} = \frac{EV_{\text{heuristic rule choice}} - EV_{\text{random rule choice}}}{EV_{\text{expected value choice}} - EV_{\text{random rule choice}}}$$

The maximum expected value possible in a particular choice set and the expected value associated with a random selection were determined. The expected value of the alternative selected by a decision heuristic was then compared to these two baseline values. This measure is bounded by a value of 1.00 for the EV rule, and an expected value of 0.0 for random selection. It provides a measure of the relative improvement of a heuristic strategy over random choice. Although this measure of accuracy may seem somewhat arbitrary, the results are not sensitive to the use of alternative criteria (see Johnson & Payne, 1985, for a discussion of other accuracy measures).

Table 1 presents the relative accuracy and effort scores for each of the 10 decision strategies in each of the four cells defined by crossing the context factors dispersion in weights (low, high) and dominance (present or absent). These scores are for the no-time-pressure conditions. The results are averaged over number of alternatives and number of attributes. Note that the aspects characterizing each strategy are also included to aid interpretation of the results.

Table 1
Simulation Results for Accuracy and Effort of Heuristics in the No-Time-Pressure Decision Problems

			Task environment			
			Dominance possible		Dominance not possible	
Strategy	Processing form	Processing selectivity	Low dispersion	High dispersion	Low dispersion	High dispersion
WADD	Alternative	No				
RA			1.0	1.0	1.0	1.0
UOC			160	160	160	160
EQW	Alternative	No				
RA			.89	.67	.41	.27
UOC			85	85	85	85
SAT	Alternative	Yes				
RA			.32	.31	.03	.07
UOC			49	49	61	61
MCD	Attribute	No				
RA			.62	.48	.07	.09
UOC			148	148	141	140
LEX	Attribute	Yes				
RA			.69	.90	.67	.90
UOC			60	60	60	60
LEXSEMI	Attribute	Yes				
RA			.71	.87	.64	.77
UOC			87	78	79	81
EBA	Attribute	Yes				
RA			.67	.66	.54	.56
UOC			87	88	82	82
EBA+WADD	Mixed	Yes				
RA			.84	.79	.69	.66
UOC			104	106	102	102
EBA+MCD	Attribute	Yes				
RA			.69	.59	.29	.31
UOC			89	89	86	86

Note. RA = relative accuracy (95% confidence interval width = ±.029). UOC = unweighted operations count (95% confidence interval width strategy. LEX = lexicographic strategy. LEXSEMI = lexicographic semi-order strategy. EBA = elimination by aspects strategy. EBA+WADD = combined elimination by aspects plus weighted additive strategy. EBA+MCD = combined elimination by aspects plus majority of confirming
combined elimination by aspects plus weighted additive strategy. EBA+MCD = combined elimination by aspects plus majority of confirming
dimensions strategy.

No-time-pressure results. The simulation results indicate that in some environments, heuristics can approximate the accuracy of a normative strategy (WADD), with substantial savings in effort. A decision maker using an EQW model, for example, can achieve 89% of the relative performance of the normative model, with only about half the effort, in the low-dispersion, dominance-possible task environment. Even more impressive is the performance of the strict lexicographic rule in the high-dispersion task environments. The lexicographic rule achieves 90% relative accuracy, with only about 40% of the effort. Note that the performance of the lexicographic-semiorder rule exceeds that of the simpler lexicographic rule in only one of the four decision environments. The extra effort needed to use JNDs may only be of value in a limited set of situations.

It is clear from Table 1 that the most efficient heuristic varies across decision environments. In the low-dispersion, dominance-possible environment, for example, the processing simplification of ignoring probability (weight) information, that is, the equal weight strategy, appears quite accurate. In contrast, when the dispersion in probabilities is higher, the lexicographic rule, which ignores all the payoff information except that associated with the single most likely outcome, is the most accurate heuristic, and is substantially better than the equal weight rule. It is also clear that some heuristics (e.g., MCD and SAT) perform reasonably in the dominance-possible environments, but are very poor performers when all dominated alternatives have been removed. Note also that in the low-dispersion, dominance-absent environment, the best simple heuristic, LEX, has an accuracy score of .67. That accuracy score is .22 less than the accuracy score for the "best" heuristic in the other three environments. This suggests that a decision maker in such an environment would not be able to reduce effort much without suffering a substantial loss in accuracy. Decision problems involving low dispersion, dominance-absent environments may therefore be particularly difficult.

In summary, heuristic strategies can be highly accurate in some environments, but no single heuristic does well across all contexts. This suggests that if a decision maker wanted to achieve both a reasonably high level of accuracy and low effort, he or she would have to use a repertoire of strategies, with selection contingent upon situational demands.

An interesting set of results from Table 1 concerns the performance of the two combined decision strategies. The combination of an elimination process with a weighted adding model (EBA+WADD) performed well across all task conditions. That rule offers a good combination of expected accuracy and reasonable levels of expected effort. The EBA+MCD rule, on the other hand, seems to be an inefficient combination strategy.

Although it is not shown in Table 1, there were systematic effects of the task variables number of alternatives and number of attributes. For example, the mean accuracy of the equal weight rule decreased only from .93 to .87 as the number of attributes increased from two to eight in the low-dispersion, dominance-possible environment. However, the mean accuracy of the LEX rule did decrease substantially, from .86 to .55, as the number of attributes was increased. The decrease in accuracy for the lexicographic rule reflects the fact that a rule that uses only information associated with a single (although the most probable) outcome would be expected to perform worse as an increasing number of relatively important (probable) outcomes are ignored. In contrast, the impact of increases in number of attributes on the EQW and LEX rules was reversed for the high-dispersion, dominance-possible environments. The mean accuracy for the EQW rule decreased from .71 to .49 for the two outcome and eight outcome problems, respectively, reflecting the fact that the rule essentially overweights information from more and more outcomes with small probabilities as the number of outcomes is increased. The LEX rule decreased only from .93 to .87 for the same problems.

The number of alternatives also had effects on effort. For instance, an increase in the number of alternatives from two to eight increased the average EIP count of the weighted adding rule by 191 EIPs. The EBA strategy, on the other hand, only increased by 79 EIPs as the number of alternatives went from two to eight. More generally, the effort required to use heuristics increased more slowly than the effort required to use more normative procedures as the number of alternatives was increased. This simulation result is compatible with prior empirical work showing shifts in strategies due to number of alternatives (Payne, 1982).

The potential trade-offs between accuracy and effort for the different strategies are highlighted by Figure 1, which shows the results from the low-dispersion in probabilities (weights), dominance possible and high-dispersion, dominance-possible contexts averaged over number of alternatives and outcomes. Only the dominance-possible context is shown because it is used in the experimental work described later. The measure of effort for each strategy has been turned into a relative measure based on the ratio of the number of EIPs required by a heuristic to the number of EIPs required by the most effortful WADD strategy. A line that indicates an efficient frontier of strategies, considering both a desire for greater accuracy and a desire for lesser effort, is drawn for each context. Figure 1 makes clear both the existence of efficient heuristics and the fact that the accuracy/effort trade-offs for various strategies differ across relatively subtle changes in context, such as the dispersion in probabilities.

The simulation does not identify which particular strategy a decision maker will necessarily select in a given decision environment. That would depend on the degree to which a decision maker was willing to trade decreases in accuracy for effort savings. However, note that if a decision maker desired relatively high levels of accuracy in an environment where dominance is possible, there are accurate strategies in each environment with substantial savings in effort: the LEX rule in the high-dispersion condition and the EQW strategy in the low-dispersion condition. Thus, the simulation predicts that when dominance is possible, one should see more processing consistent with a LEX strategy (e.g., attribute-based processing, selective processing across attributes, and higher proportions of processing on probabilities and the most important attribute) in environments with high-dispersion in probabilities. In contrast, in low-dispersion environments, one should observe more alternative-based processing, more consistent processing, and a lower proportion of processing of probabilities and the most important attribute, consistent with strategies like the EQW rule. The prediction is based on the assump-

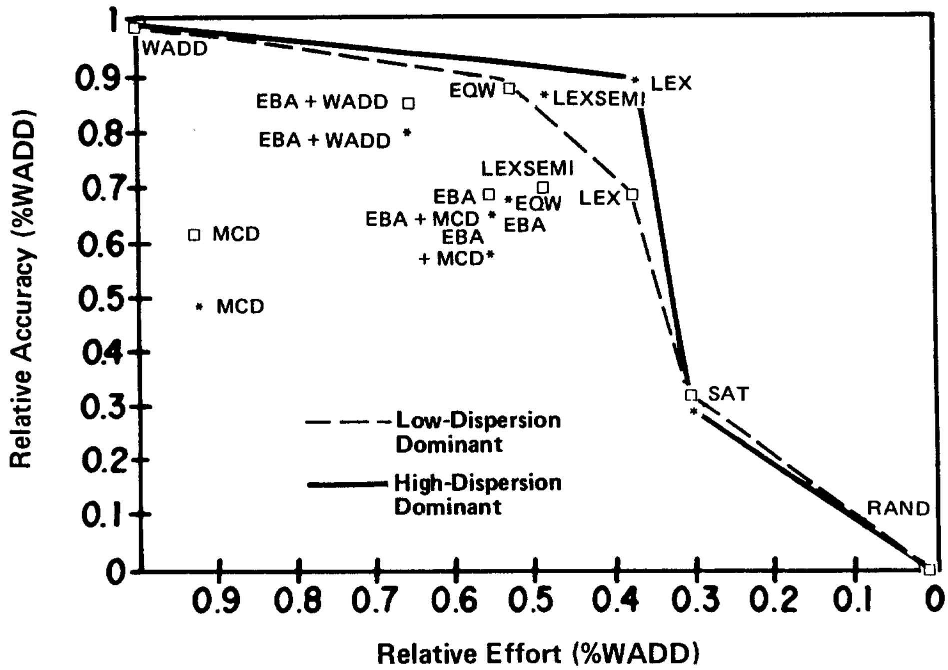

Figure 1. Effort/accuracy trade-offs for various decision strategies in the low-dispersion and high-dispersion dominance-possible environments.

tion that *people are sensitive to the relative accuracy of strategies in different contexts,* as well as being aware of differences in relative effort.

In addition to this prediction, a more subtle prediction can also be made. Note that if one uses the equal weight strategy in a low-dispersion environment and the LEX strategy under high dispersion, roughly equal accuracy can be attained. However, less effort is required in the high-dispersion environment. Thus, if subjects desire relatively high levels of accuracy, the simulation would predict that accuracy levels would not vary across dispersion conditions, but that effort levels would be lower for the high-dispersion condition.

The simulation results discussed so far have assumed as a first approximation that all EIPs require an equal amount of effort to execute. Prior work by Johnson and Payne (1985) suggested that such an assumption was sufficient for the simplified decision tasks they studied. However, it does seem reasonable that some EIPs may take more time to execute, or be more effortful, than others. In another study, Bettman et al. (1987) used counts of elementary operations (EIPs) to

Table 2
Simulation Results for Accuracy of Heuristics Under Time Pressure

			Task environment											
			Dominance possible						Dominance not possible					
			Low dispersion			High dispersion			Low dispersion			High dispersion		
Strategy	Processing form	Processing selectivity	LTP	MTP	STP	LTP	MTP	STP	LTP	MTP	STP	LTP	MTP	STP
WADD	Alternative	No	.91[a]	.80	.28	.91[a]	.80	.28	.90[a]	.77[a]	.12	.92[a]	.82	.24
EQW	Alternative	No	.88	.82[a]	.72[a]	.66	.65	.55	.41	.34	.26	.24	.25	.18
SAT	Alternative	Yes	.38	.34	.30	.32	.34	.23	.03	.04	.06	.07	.05	.04
MCD	Attribute	No	.58	.49	.23	.44	.35	.17	.03	−.01	−.02	.04	.03	.02
LEX	Attribute	Yes	.70	.69	.47	.90	.90[a]	.59	.69	.68	.48[a]	.90	.90[a]	.60
LEXSEMI	Attribute	Yes	.71	.66	.40	.87	.83	.49	.63	.59	.43	.76	.75	.51
EBA	Attribute	Yes	.70	.68	.49	.76	.73	.65[a]	.63	.60	.48[a]	.67	.67	.61[a]
EBA+WADD	Mixed	Yes	.86	.79	.43	.86	.82	.48	.73	.66	.27	.75	.74	.43
EBA+MCD	Attribute	Yes	.74	.65	.44	.67	.60	.49	.35	.32	.27	.40	.41	.36

Note. The 95% confidence interval width for the accuracy values is ± .029. LTP = low time pressure. MTP = moderate time pressure. STP = severe time pressure. WADD = weighted additive strategy. EQW = equal weight strategy. SAT = satisficing strategy. MCD = majority of confirming dimensions strategy. LEX = lexicographic strategy. LEXSEMI = lexicographic semi-order strategy. EBA = elimination by aspects strategy. EBA+WADD = combined elimination by aspects plus weighted additive strategy. EBA+MCD = combined elimination by aspects plus majority of confirming dimensions strategy.
[a] The most accurate strategy for each task environment.

predict measures of decision effort such as the total time required to make a decision. The counts of EIPs required by a specific strategy for a specific decision problem provided an excellent ($R^2 = .81$) prediction of overall decision latencies. Consequently, estimates of the times associated with the EIPs obtained by Bettman et al. were used to see if the trade-offs between accuracy and effort for the different strategies examined in the present study would change. The major result was that all the heuristics become relatively less effortful when the individual EIPs are weighted. However, the aforementioned key relations between aspects of processing and the context variable of low and high dispersion are essentially unchanged when weighted effort counts were used in place of the equal weighted assumption. The relative performance of the various strategies was almost identical.

Time pressure results. The time pressure results are shown in Table 2. Time constraints clearly have differential effects on the various rules. The WADD rule, for example, shows a marked reduction in accuracy from the baseline value of 1.0 under no time pressure to an average accuracy of only .12 under the most severe time constraint in the no-dominance, low-dispersion condition. In contrast, the EBA heuristic shows relatively little effect of time pressure. The average accuracy across environments is reduced only from .69 with no time pressure to .56 under severe time pressure. Interestingly, the EBA rule is actually the most accurate decision strategy in three of the four environments for severe time pressure. The LEX rule also holds up well under time pressure. It appears that strategies involving an initial processing of all alternatives using a limited set of attributes do well under severe time pressure. On the basis of the simulations, it seems important under high time pressure to use a choice strategy that processes at least *some* information about *all* alternatives as soon as possible. However, note that in one decision environment (dominance possible, low dispersion in weights), the alternative simplification strategy provided by the equal weight rule is superior for even the most severe time constraint studied.

Implications of the Simulation

The simulation results indicate what a decision maker might do to adapt to various decision environments. The results clearly suggest the possibility that a decision maker might maintain a high level of accuracy *and* minimize effort by using a diverse set of heuristics, changing rules as contexts and time pressures change.

Obviously, the simulation results have to be interpreted with some caution. Although the results appear to be robust, both the measures of effort and the measures of accuracy represent approximations. In addition, it is unlikely that actual choice behavior involves a straightforward execution of one choice strategy or another. As noted earlier, there is evidence for mixtures of strategies being used (Payne, 1976). The strategies represented in the simulation should be viewed as prototypical strategies that can be used to hypothesize how the form of information processing in decision making may shift as a function of task and context demands.

Despite these limitations, the simulation work provides insights into how processing might change if efficient accuracy–effort trade-offs were desired. The simulation results for the context variable, dispersion in probabilities, suggest that when dominated alternatives are possible, more attribute-based processing, more selective processing across attributes and alternatives, and a higher proportion of processing on probabilities and the most important attribute should be observed in the high-dispersion rather than in the low-dispersion condition. Such aspects characterize rules, like the LEX rules, that are relatively accurate with substantial effort savings in the high-dispersion environment. In addition, it was noted earlier that individuals should be able to attain similar levels of accuracy in both low- and high-dispersion environments, but they should be able to do so with less effort in the high-dispersion setting.

The simulation also suggests that strategies characterized by attribute-based processing and selectivity in processing, particularly across attributes, should be more effective under severe time pressure. Strategies such as LEX and EBA, which maintain accuracy relatively well under heavy time pressure, also are characterized by a greater proportion of processing on probabilities and the most important attribute.

The foregoing simulation work could be validated in several ways. One method, used in Bettman et al. (1987), as noted earlier, is to show that counts of the elementary operations generated by the simulation could be used to predict effort-related behaviors such as the total time required to make a decision or self-reports of cognitive effort. Another approach to validation would be to show that adaptivity in information processing shown by human decision makers, when free to select any strategy, was in the general directions predicted by the simulation. The next two experiments take this second approach to validation and investigate the adaptivity of processing when actual decision behavior is examined.

Empirical Investigations: An Overview

The following experiments examine the degree of correspondence between the actual adaptivity shown by human decision makers and the adaptive processing patterns (strategies) implied by the simulation results. Specifically, we ask (a) to what extent do people vary their information processing behavior as a function of context effects such as the dispersion of probabilities and task effects such as time pressure?; and (b) are these changes in processing in the directions suggested by the simulation? One important feature of these experiments is the use of a complete within-subjects design. Such a design provides a strong test of adaptivity, because the subject would be expected to switch strategies from one trial to the next.

As outlined earlier the simulation results provide a fairly clear picture of an adaptive decision maker. If decision makers adapt as suggested by the simulation, there should be a relation between the dispersion of probabilities and various aspects of processing. In particular, more attribute-based processing, greater selectivity in processing across attributes and alternatives, and a greater proportion of processing devoted to probabilities and the most important attribute are expected in a high-dispersion environment. Such shifts in processing as a function of context would indicate that people are sensitive to changes in choice environments that affect the accuracy of strategies and not just to changes that affect processing demands. The reason is that the relative accuracy of rules varies across contexts (dispersion conditions), but the relative 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 fairly common (see Payne, 1982); studies showing processing changes due to context variables, and hence implicitly some concern for accuracy, are much less common (however, see Busemeyer, 1985; Russo & Dosher, 1983).

The task variable examined is the presence or absence of time pressure. The simulation results also indicate changes in aspects of processing under severe levels of time pressure. In particular, more attribute-based processing, greater selectivity in processing, and a greater proportion of processing focused on probabilities and the most important attribute might be expected.

Other work on time pressure reinforces these predictions. For example, Ben Zur and Breznitz (1981) identified at least three ways in which people may respond to time constraints. One way to cope with time pressure is to process only a subset of the most important information, an idea referred to as "filtration" (Miller, 1960). Another way to cope with time pressure is to "accelerate" processing (Ben Zur & Breznitz, 1981; Miller, 1960) by trying to process the same information at a faster rate. Finally, one could shift processing strategies. At the extreme, this could involve random choice, or "avoidance" (Ben Zur & Breznitz, 1981; Miller, 1960). A less extreme form of contingent processing would involve a shift from a more effortful rule, such as the additive rule, to a less effortful rule, like EBA. The simulation results indicate that such a strategy shift could maintain relatively high levels of accuracy, even under severe time pressure.

The hypothesis of filtration is supported in other studies. For example, Wright (1974) reported that the most important information in a judgment task was given more weight under time pressure. Ben Zur and Breznitz (1981) reported shifting to the use of more important information under time pressure. Furthermore, Ben Zur and Breznitz also found that subjects spent less time looking at individual items of information under time pressure. They concluded that combining filtration and limited acceleration "can be viewed as the optimal decision making strategy when the [decision maker] is confronted with information overload while pressured by deadlines" (p. 102). Note that filtration can be characterized by greater selectivity across alternatives and attributes and by greater emphasis on the most important attribute.

The foregoing hypotheses deal with processing information. Accuracy under time pressure was addressed by Zakay and Wooler (1984). 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 sum, the simulation and prior empirical research lead to several hypotheses. Both higher dispersion in probabilities and higher time pressure are expected to lead to greater use of attribute-based processing, greater selectivity across attributes and alternatives, and greater focus of processing on probabilities and the most important attribute. In addition, there should be no difference in accuracy for different levels of dispersion, but there should be less effort under high dispersion. Under high time pressure, accuracy should be lower and information should be processed more rapidly.

These predictions could be derived in at least two ways. One could assume that subjects have explicit accuracy and effort feedback and make conscious trade-offs of accuracy and effort. Alternatively, one can assume that subjects have general knowledge of the properties of a reasonable strategy and of task environments (e.g., see Reder, 1987). Then, in the course of making decisions, subjects generate *process feedback* (Anzai & Simon, 1979). That is, subjects can ascertain how effortful their strategy was and how closely it resembled their notion of what a "good" strategy should entail. Such process feedback can be generated without explicit feedback about outcomes. Subjects would then adapt based upon their general knowledge and process feedback (Reder, 1987).

In the present article, the second mode of arriving at the predictions was used. Subjects are assumed to have ideas about the characteristics of reasonable strategies, to generate process feedback, and to adapt by using the process feedback and seeing how well their strategy as executed matches their view of a "reasonable" strategy. In the experiments reported, the choices are made without explicit feedback regarding accuracy for two major reasons: (a) The majority of common decision problems do not offer the opportunity to receive immediate and clear feedback about the quality of choice (Einhorn, 1980); (b) to the extent adaptivity is exhibited in situations without explicit accuracy feedback, it provides strong evidence for adaptive decision processing. That is, it would suggest that adaptivity may be crucial enough to decision makers that they will guide themselves to it without the need for an external prod in the form of explicit feedback.

Experiment 1

In this experiment, the extent of adaptivity to changes in the dispersion of probabilities and to the presence or absence of time pressure was tested. The main hypotheses are that people will adapt their behavior to the demands of the decision environment in accordance with the general patterns identified by the simulation.

Method

Subjects. A total of 16 undergraduates at Duke University served as subjects. 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 four risky options. Each option in a set offered four possible outcomes (attributes). The outcomes involved possible payoffs ranging from $0.01 to $9.99. Every option in a set was defined in terms of the same four outcome probabilities. The probabilities for any given outcome ranged from .01 to .96, with the constraint that the four outcome probabilities summed to one.

Ten sets of high dispersion in probabilities (weights) options and 10 sets of low dispersion options were generated, with dominated options allowed in all sets. In terms of the design used for the simulation study, sets of options were sampled from the low-dispersion, dominance-possible and high-dispersion, dominance-possible conditions. To illustrate, one low-dispersion set of gambles had probabilities of .22, .26, .24, and .28 for the four possible outcomes. Gamble A provided payoffs of \$8.73, \$7.83, \$1.74, and \$8.91, respectively, for the four outcomes. Gamble B provided payoffs of \$7.54, \$4.64, \$5.11, and \$6.73. Gambles C and D had different, but similar types of payoffs. One high-dispersion set of options, on the other hand, had probabilities of .20, .04, .07, and .69. The payoffs for Gamble A were \$6.86, \$1.18, \$4.96, and \$0.84, respectively. Gamble B had payoffs of \$1.38, \$3.34, \$8.49, and \$2.91, respectively. Again, Gambles C and D were similar. Overall, the sets of options in the low- and high-dispersion conditions were equivalent in terms of their average expected values.

The 20 sets of options (10 low dispersion, 10 high dispersion) were randomly presented under two time pressure conditions. One involved no explicit time pressure. Subjects 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-s time constraint. In this condition, a clock was shown in the upper-left corner of the display with the information about the gambles (described more fully below). As the 15 s passed, the clock slowly disappeared. At 15 s, a beep sounded, the subject could not acquire additional information, and he or she was instructed to make a choice. For comparison, a pilot study indicated that subjects took about 50 s, on average, when under no time pressure. In the experiments reported below, subjects averaged approximately 44 s per trial when under no time pressure.

There were 40 decision problems (2 context conditions × 2 time pressure conditions × 10 replications) presented to each subject in random order, with the same random order used for all subjects. A complete experimental session took 30–45 min for each subject.

The Mouselab methodology. Information acquisitions, response times, and choices were monitored using a software system called *Mouselab* (Johnson, Payne, Schkade, & Bettman, 1986). This system uses an IBM personal computer, or equivalent, equipped with a "mouse" for moving 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 2 is an example of a stimulus display with one box opened, and with the time pressure clock part way through the countdown.

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, the subject has

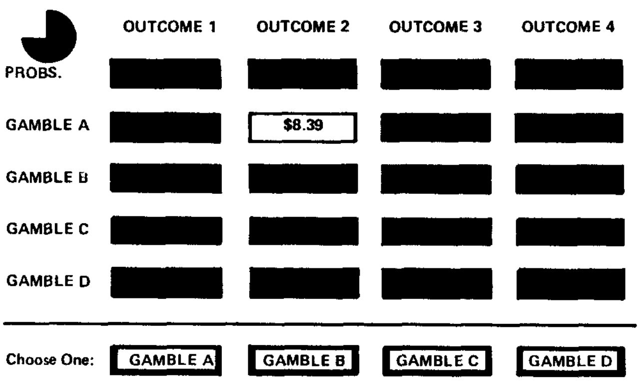

Figure 2. Example of stimulus display using the *Mouselab* system with time-pressure clock.

to 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, the amount of time boxes are open, the chosen option, and 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's Law indicates that one could move between boxes in less than 100 ms (Card et al., 1983). 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. Although the use of such a process-tracing system itself could possibly induce a change in strategies, recent research using the *Mouselab* system has replicated findings (e.g., preference reversals) found in studies that do not use such a process-tracing mechanism (Johnson, Payne, & Bettman, in press). There might also be concern that the tabular format is unnatural. However, tables of information appear in such magazines as *Consumer Reports*, and many computer-based decision aids also use a similar format.

Dependent measures. Information acquisition and decision behavior can be characterized in many ways. One can examine the amount and sequence of information acquired, and the time spent acquiring information (Klayman, 1983). To examine the aforementioned hypotheses, we consider seven measures of aspects of decision processing. One important aspect is the total amount of processing. One measure of amount is the total number of times information boxes were opened for a particular decision, denoted acquisitions (ACQ). A second measure, which is related to the amount of processing effort and is also directly relevant to the hypothesis of acceleration of processing under time pressure, is the average time spent per item of information acquired (TPERACQ).

The next several measures reflect the relative attention devoted to specific types of information, and hence are relevant to characterizing selectivity in processing and the related concept of filtration. One measure, denoted PTMI, is the proportion of the total time acquiring information that was spent in boxes involving the most important attribute of a particular decision problem. The attribute (outcome) with the largest weight (probability of occurrence) was defined to be 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 next two measures are the variances in the proportions of time spent on each alternative (VAR-ALTER) and on each attribute (VAR-ATTRIB). Such variances are related to selectivity. As described earlier more compensatory decision rules (e.g., WADD, EQW, and MCD) imply a pattern of information acquisition that is consistent (low in variance) across alternatives and attributes; in contrast, noncompensatory strategies, like EBA, LEX, and SAT, imply more variance in processing.

A final measure of processing characterizes the sequence of information acquisitions relating to outcome values. Given the acquisition of a particular piece of information, two particularly relevant cases for the next piece of information acquired involve the same alternative but different attribute (an alternative-based, holistic, or Type 1 transition), and the same attribute but a different alternative (an attribute-based, dimensional, or Type 2 transition). 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, denoted PATTERN, ranges from a value of −1.0 to +1.0. A more positive number indicates relatively more alternative-based processing, and a more negative number indicates relatively more attribute-based processing.

In addition to these seven measures of processing, a measure of relative accuracy, defined as above in terms of EV maximization and random choice, was developed and denoted GAIN.

These measures can be related directly to the hypotheses outlined previously. Higher dispersion in probabilities and higher time pressure should lead to lower values of PATTERN (more attribute-based processing); higher values of VAR-ALTER and VAR-ATTRIB (greater selectivity); and higher values of PTPROB and PTMI (greater focus on probabilities and the most important attribute). In addition, there should be fewer acquisitions (ACQ) and lower TPERACQ under high dispersion (less processing effort), and TPERACQ should be lower under time pressure. Finally, GAIN should be similar across levels of dispersion, but lower under high time pressure.

Procedure. Each subject was told that the purpose of the experiment was to understand how people make decisions, that there were no objectively "right" or "wrong" choices, and that the "best" action was to choose that risky option they would most prefer to play. Subjects were also 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. Thus, the subjects could win between \$0.01 and \$9.99, depending on their choices and the random process.

Subjects then were instructed on 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 and that some decisions would involve an explicit time constraint, whereas for other decision problems they could take as long as they wished.

Results

Overview. The main focus in the results concerns how people adapt to the task manipulation of time pressure and the context manipulation of dispersion in probabilities. Effects are examined for the foregoing four main types of dependent measures: amount of processing, selectivity in processing, pattern of processing, and relative accuracy.

To provide the strongest possible test of adaptivity, a within-subjects experimental design was used. Subjects, however, may have to experience several examples of different types of decision problems before settling on a preferred strategy for a particular type of problem. Consequently, the results are presented both for the block of 20 decision problems seen first by the decision maker, and the block of the last 20 decisions. Problems corresponding to each of the four time-pressure–dispersion combinations were distributed essentially equally over the two blocks.

A multivariate analysis. Given the likely correlations among the various process measures, the data were first analyzed using a multivariate analysis of variance with three within-subject factors (dispersion, time pressure, and block). The analysis included the aforementioned seven process measures plus the measure of relative accuracy, denoted GAIN. The means for these measures are presented in Table 3. Overall, the main effects of dispersion, $F(8, 606) = 21.54$, time pressure, $F(8, 606) = 62.98$, and block, $F(8, 606) = 6.28$, were highly significant ($p < .001$). There was a significant dispersion by time pressure interaction, $F(8, 606) = 4.05$, $p < .001$, and an interaction of time pressure with block, $F(8, 606) = 5.38$, $p < .001$. There was no interaction of block and dispersion, $F(8, 606) = 1.20$, *ns*, although there was a significant three-way interaction of block by dispersion by time pressure, $F(8, 606) = 3.05$, $p < .01$.

To more fully characterize the effects of dispersion, time pressure, and block, separate univariate analyses of variance were conducted for each of the dependent measures. The results presented in Table 3 will first be discussed in terms of dispersion in probabilities (a context effect), then for time pressure (a task effect), and then briefly for block. Interactions involving block are considered where relevant. Within each section, the results are presented for the amount of processing measures (ACQ and TPERACQ), then for the selectivity measures (PTMI, PTPROB, VAR-ATTRIB, and VAR-ALTER), and then the PATTERN measure. A summary of results at the individual subject level is briefly presented, and then the GAIN measure is discussed.

Effects of dispersion. High dispersion was predicted to lead to fewer acquisitions (ACQ), less time per acquisition (TPERACQ), greater focus on the most important dimension (PTMI) and on probabilities (PTPROB), higher selectivity for attributes

Table 3
Summary of Process Measures and GAIN *as a Function of Time Pressure, Context, and Decision Block: Experiment 1*

Dependent measure	No time pressure				Time pressure = 15 s			
	Low dispersion		High dispersion		Low dispersion		High dispersion	
	Block 1	Block 2	Block 1	Block 2	Block 1	Block 2	Block 1	Block 2
ACQ	46.6	35.3	35.1	27.6	18.3	17.6	15.6	15.4
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
VAR-ALTER	.010	.011	.011	.016	.012	.012	.013	.012
VAR-ATTRIB	.011	.013	.021	.035	.013	.018	.031	.035
PATTERN	−.111	−.107	−.319	−.329	−.103	−.164	−.446	−.408
GAIN	.694	.609	.585	.611	.269	.616	.398	.643

Note. ACQ = number of information boxes examined. TPERACQ = time per information acquisition. PTMI = proportion of time on the most important attribute. PTPROB = proportion of time on the probability information. 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). PATTERN = index reflecting relative amount of attribute-based (−) and alternative-based (+) processing. GAIN = relative accuracy of choices.

(VAR-ATTRIB) and alternatives (VAR-ALTER), and more attribute-based processing (lower values of PATTERN). There was no effect expected on GAIN. The dispersion manipulation generally showed these effects.

As predicted, there was a significant difference between low and high dispersion for both the number of acquisitions (ACQ) ($M = 28.90$ vs. $M = 23.82$), $F(1, 617) = 36.39$, $p < .001$, and time per acquisition ($M = .60$ vs. $M = 57$), $F(1, 617) = 7.21$, $p < .001$. Less effort was used in reaching a decision for the high-dispersion problems. The only significant dispersion by time pressure interactions were for ACQ, $F(1, 617) = 12.91$, $p < .001$, and TPERACQ $F(1, 617) = 12.56$, $p < .001$. The effect of dispersion is greater in the no-time-pressure problems.

The pattern of results for the variables related to selectivity also was largely as predicted. There was more focus on the dimension associated with the largest probability (PTMI) with high dispersion of probabilities ($M = .34$ vs. $M = .44$), $F(1, 617) = 92.34$, $p < .001$.[2] However, contrary to prediction, there was no significant difference in the proportion of time spent on probabilities ($M = .27$ vs. $M = .27$), $F(1, 617) = 1.34$, *ns*. Both the variance in processing across attributes (VAR-ATTRIB) and across alternatives (VAR-ALTER), on the other hand, increased significantly for the high-dispersion problems ($M = .014$ vs. $.030$), $F(1, 617) = 119.13$, $p < .001$, ($M = .011$ vs. $M = .013$), $F(1, 617) = 7.14$, $p < .05$, respectively. Thus, one effect of increased dispersion was to increase the amount of selectivity in processing, which is consistent with the use of heuristic processes such as the LEX or EBA strategies.

The hypothesis of a shift in strategies due to the context manipulation is also supported by the fact that the amount of attribute-based processing (shown by negative values of PATTERN) increased significantly as the dispersion of probabilities increased ($M = -.12$ vs. $-.37$), $F(1, 613) = 54.60$, $p < .001$. This result for PATTERN is consistent with greater use of strategies such as EBA or the lexicographic rule for high dispersion in probabilities.

The foregoing results are averaged across subjects. Individual subjects showed patterns similar to those reported above. For example, 86% of the subjects acquired less information in the high-dispersion condition. Seventy-five percent spent less time per acquisition for high-dispersion problems. One hundred percent of the subjects spent more time on the most important attribute, 56% spent more time on probabilities, 100% had greater variance in processing across attributes, and 82% had greater variance in processing across alternatives for the high-dispersion problems. More attribute-based processing was shown by 82% of the subjects in the high-dispersion condition than in the low-dispersion condition. Thus, both group and individual analyses show adaptivity in process as a function of context.

Finally, as expected, the average GAIN scores for the low-dispersion and high-dispersion problems did not differ significantly ($M = .54$ vs. $M = .56$), $F(1, 617) = .06$, *ns*. The accuracy of the processes used in the two contexts was approximately the same.

The simulation results suggest that an adaptive decision maker could take advantage of changes in context to maintain accuracy with substantially less processing effort. The experimental results clearly demonstrate a shift in processing strategies with variation in context. People demonstrated an ability to shift processing to take advantage of problem structure so as to reduce processing load while maintaining accuracy. The empirical support for this relatively subtle prediction of the simulation provides strong support for the current approach. Previous work on contingent decision behavior has most clearly demonstrated a sensitivity to effort, such as the effects of variations in the number of alternatives or attributes (Payne, 1982). The present work demonstrates an ability to maintain accuracy even under a subtle change in context, as well as sensitivity to effort.

Effects of time pressure. High time pressure was predicted to lead to lower values for ACQ and TPERACQ; higher values for PTMI, PTPROB, VAR-ATTRIB, and VAR-ALTER; a lower value for PATTERN; and a lower value for GAIN.

As expected, subjects acquired fewer items of information (ACQ) in the time-constrained choice environments ($M = 35.98$ vs. $M = 16.74$), $F(1, 617) = 378.44$, $p < .001$. This finding was qualified by a block by time pressure interaction, $F(, 617) = 20.15$, $p < .001$, which showed that the amount of information acquisition did not vary over blocks in the high-time-pressure condition, but that the amount of information acquired in the second block was less than that acquired in the first block under no time pressure.

One major hypothesis regarding time pressure and decision making is that people adapt to time constraints by accelerating their processing. The results for the time per acquisition variable (TPERACQ) indicate that people did process information significantly faster under time pressure ($M = .67$ s vs. $M = .48$ s), $F(1, 617) = 217.36$, $p < .001$. A block by time pressure interaction, $F(1, 617) = 3.87$, $p < .05$, showed that a decrease over blocks only occurred in the no-time-pressure condition. These results are consistent with those of Ben Zur and Breznitz (1981).

The results for the variables related to selectivity and filtration also supported the hypotheses. The proportion of time spent on the most important attribute (most likely outcome; PTMI) was significantly greater under time pressure ($M = .37$ vs. $M = .41$), $F(1, 617) = 9.83$, $p < .01$. The proportion of time spent on probabilities (PTPROB) was also greater for the time-pressured problems ($M = .25$ vs. $M = .29$), $F(1, 617) = 18.14$, $p < .001$, clearly supporting the filtration hypothesis.

Greater selectivity in processing under time pressure was also indicated by greater variance in processing the attributes (VAR-ATTRIB) with a time constraint ($M = .019$ vs. $M = .024$), $F(1, 617) = 5.98$, $p < .05$. Interestingly, there was no effect of time pressure on the amount of variance in processing across alternatives, ($M = .30$ vs. $M = .31$), $F(1, 617) = .06$, *ns*. Although the lack of results for VAR-ALTER is not as hypothesized, the results for PTMI, PTPROB, and VAR-ATTRIB support the notions of increasing filtration and selectivity under time pressure.

Further evidence for a shift in information processing strategy as a function of time pressure is provided by the results

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[2] Analyses of variance for PTMI and PTPROB were also run with both measures transformed by an arc sine transformation. The results were essentially the same, and the untransformed results are reported for simplicity.

for PATTERN of processing. Under time constraint, processing became marginally more attribute based ($M = -.22$ vs. $M = -.28$), $F(1, 617) = 3.55$, $p = .06$.

To summarize, the results showed that people adapted to time pressure by accelerating processing, increasing the selectivity of processing, and moving toward more attribute-based processing. The latter two effects, taken together, are consistent with the greater use of heuristics like the LEX or EBA strategy under time pressure.

Again, the means for each individual showed that a majority of subjects responded in the same directions as indicated by the group analysis. For instance, 100% of the subjects accelerated processing under time constraint (ACQ and TPERACQ). Sixty-nine percent showed evidence of filtration as indicated by PTMI and VAR-ATTRIB. Sixty-three percent demonstrated a greater focus on probabilities, 44% showed higher values for VAR-ALTER, and 63% demonstrated more attribute-based processing under time constraints.

In addition to time pressure effects on processing, there was a clear impact of time constraint on accuracy. Relative accuracy was lower under time pressure ($M = .62$ vs. $M = .48$), $F(1, 617) = 8.32$, $p < .01$. An examination of the pattern of means in Table 3, however, makes it clear that the decrement in performance is concentrated in the responses to the earlier (first block) problems involving time pressure. By the latter block, performance had improved to levels similar to those obtained in the no-time-pressure condition, as verified by a significant block by time pressure interaction, $F(1, 617) = 10.73$, $p < .01$.

Discussion

The central conclusion from the results of Experiment 1 is that people exhibit a substantial degree of adaptivity in their decision behavior. Decision processes were sensitive to a context variable that influences the relative accuracy of heuristics. Decision processes were also sensitive to the important task variable of time pressure. Across a variety of dependent measures, the pattern of results supported the predictions. These findings of adaptivity are particularly strong in that they were exhibited by the same subjects on different trials. Finally, the general pattern of adaptive behavior was consistent with the simulation results.

The time-pressure results supported the hypotheses that increased time pressure wold result in (a) acceleration of information processing, (b) filtration of information to be processed, and (c) to a lesser extent, changes in the choice heuristics used to make a decision. Prior research has supported the acceleration and filtration hypotheses, but the present experiment also suggests changes in information processing strategies as a function of time pressure.

The existence of 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 pressure? 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 next experiment investigates that possibility by examining a case of less severe time pressure.

Experiment 2

This study examines the extent and direction of adaptive decision processing when the amount of time pressure is less severe than that investigated in Experiment 1. Specifically, one time pressure condition in this study used a 25-s limit. For comparison, and also for purposes of replication, a second time pressure condition used the 15-s limit used in Experiment 1. Furthermore, subjects in this study returned for a second day. During the second session, the experiment was repeated, but with the time pressure level set at 25 s if a subject had received 15 s on the first day or set at 15 s if a subject had 25 s on the first day. The inclusion of the second session was intended to explore how adaptivity to one choice environment might influence adaptivity to a slightly different choice environment. Finally, this study again examined the effects of dispersion in probabilities.

Method

Subjects. A total of 28 undergraduate students served as subjects in this experiment in return for course credit and the chance to win money. Because this experiment involved two different experimental sessions, the maximum amount of money that could be won was $19.98 ($9.99 for each session).

Stimuli and procedures. The stimuli and procedures used in this study were essentially the same as those used in Experiment 1. For the first session, subjects were randomly assigned to one of two groups: time pressure = 15 s (Group 1) or time pressure = 25 s (Group 2). Owing to computer problems, cell sizes were unequal, with 16 subjects in Group 1 and 12 subjects in Group 2. One difference in instructions from the previous experiment was that subjects were told how much time was involved in the time pressure trials. After the end of the first session, a gamble preferred by the subject was selected, but not played. The second session had the time pressure set at the level opposite to that received on the first day. Also, the order of the outcomes and alternatives was permuted for the sets of gambles to reduce the possibility that the subject would remember the particular choice problems from the previous day.

Results

The measures of process and accuracy used in this study were the same as those used in the previous experiment. Table 4 presents the means for each of the seven process measures and GAIN as a function of day, group, presence/absence of time pressure, and low versus high dispersion. The data were analyzed with a five within-subjects factor multivariate analysis of variance (presence of time pressure, dispersion, block, day, and level of time pressure: 25 s vs. 15 s). Subjects was treated as a factor nested within day and level.

The multivariate analysis of variance showed significant effects of dispersion, $F(8, 2147) = 116.24$, $p < .001$, and presence of time pressure, $F(8, 2147) = 200.64$, $p < .001$. In addition, the main effects of day, $F(8, 2147) = 21.42$, level of time pressure, $F(8, 2147) = 18.16$, and block, $F(8, 2147) = 23.63$, were all significant ($p < .001$).

The two-way interactions were generally significant as well. Of most interest were a presence of time pressure by dispersion

Table 4
Summary of Process and Accuracy Results: Experiment 2

Dependent measure	Day 1 Results: Group 1 (N = 16) NTP Low dispersion	NTP High dispersion	TP = 15 s Low dispersion	TP = 15 s High dispersion	Group 2 (N = 12) NTP Low dispersion	NTP High dispersion	TP = 25 s Low dispersion	TP = 25 s High dispersion
ACQ	50.8	42.1	19.5	17.2	52.8	45.2	28.8	27.7
TPERACQ	.64	.62	.48	.48	.64	.62	.52	.52
PTMI	.29	.37	.32	.43	.30	.39	.32	.41
PTPROB	.24	.27	.27	.29	.19	.20	.20	.22
VAR-ALTER	.010	.013	.009	.013	.008	.010	.008	.010
VAR-ATTRIB	.007	.018	.013	.027	.005	.017	.007	.021
PATTERN	.00	−.22	−.03	−.31	.30	.00	.33	.03
GAIN	.56	.59	.43	.42	.75	.81	.67	.64

Dependent measure	Day 2 Results: NTP Low dispersion	NTP High dispersion	TP = 25 s Low dispersion	TP = 25 s High dispersion	NTP Low dispersion	NTP High dispersion	TP = 15 s Low dispersion	TP = 15 s High dispersion
ACQ	48.6	36.6	27.7	24.2	42.0	36.4	21.0	19.0
TPERACQ	.58	.56	.49	.49	.57	.54	.46	.47
PTMI	.28	.39	.27	.41	.30	.39	.30	.43
PTPROB	.22	.26	.22	.27	.19	.21	.20	.23
VAR-ALTER	.010	.013	.008	.014	.009	.011	.009	.011
VAR-ATTRIB	.006	.020	.006	.021	.005	.020	.007	.026
PATTERN	.13	−.11	.22	−.08	.39	−.02	.45	−.06
GAIN	.66	.57	.59	.52	.74	.75	.65	.58

Note. NTP = no time pressure. TP = time pressure. ACQ = number of information boxes examined. TPERACQ = time per information acquisition. PTMI = proportion of time on the most important attribute. PTPROB = proportion of time on the probability information. 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). PATTERN = index reflecting relative amount of attribute-based (−) and alternative-based (+) processing. GAIN = relative accuracy of choices.

interaction, $F(8, 2147) = 54.13$, $p < .001$, a presence of time pressure by block interaction, $F(8, 2147) = 10.39$, $p < .001$, and a day by level of time pressure interaction, $F(8, 2147) = 54.13$, $p < .001$. The first two interactions are consistent with those obtained in Experiment 1. The latter interaction suggests that it did matter whether a subject received the 15-s (severe time pressure) problems on the first or second day.

Analyses of simple effects within the 15-s and 25-s time-pressure groups were performed. Because the major focus of Experiment 2 was on time-pressure effects, those results are discussed first, followed by results for dispersion. Then effects of day and level are briefly considered. The predictions for the various dependent variables are the same as in Experiment 1.

Time pressure effects. The results most comparable to Experiment 1, of course, are the first-day results. An examination of the first-day process means for Group 1 (time pressure = 15 s) and Group 2 (time pressure = 25 s), reported in Table 4, indicates that the previous findings for 15 s did replicate, and that there may be a hierarchy of responses to levels of time pressure.

An analysis of simple effects for the variables related to amount of processing showed fewer acquisitions with time pressure present for both the 15-s ($M = 46.43$ vs. $M = 18.38$), $F(1, 2154) = 507.01$, $p < .001$, and the 25-s conditions ($M = 49.03$ vs. $M = 28.25$), $F(1, 2154) = 209.82$, $p < .001$. There was also less time per acquisition under time pressure in both cases: 15-s condition ($M = .63$ vs. $M = .48$), $F(1, 2154 = 394.92$, $p < .001$; 25-s condition ($M = .63$ vs. $M = .52$), $F(1, 2154) = 156.88$, $p < .001$. Thus, both time pressure levels show evidence consistent with acceleration of processing.

Analyses of simple effects for the amount of filtration and selectivity in processing show similar patterns within the 15-s and 25-s time-pressure conditions for the first day. However, the results for the 15-s level of time pressure are generally stronger. For the 15-s level, there were effects of time pressure on PTMI ($M = .33$ vs. $M = .37$), $F(1, 2154) = 22.86$, $p < .001$, PTPROB ($M = .25$ vs. $M = .28$), $F(1,2154) = 11.76$, $p < .001$, and VAR-ATTRIB ($M = .013$ vs. $M = .020$), $F(1, 2154) = 37.37$, $p < .001$. There was no effect on VAR-ALTER ($M = .011$ vs. $M = .011$), $F(1, 2154) = .02$, *ns.* There was an effect of time pressure for the 25-s level on PTMI ($M = .34$ vs. $M = .37$), $F(1, 2154) = 4.99$, $p < .05$, and marginal effects for PTPROB ($M = .20$ vs. $M = .21$), $F(1, 2154) = 3.71$, $p < .06$, and VAR-ATTRIB ($M = .011$ vs. M .014), $F(1, 2154) = 3.66$, $p < .06$. There was no effect on VAR-ALTER ($M = .009$ vs. $M = .009$), $F(1, 2154) = .26$, *ns.* Thus, there is evidence for selectivity under both time pressure conditions, although there appears to be more selectivity when time pressure is severe.

Of greatest importance for the hypothesis of a hierarchy of time pressure effects was the finding of a significant effect of time pressure on pattern of processing in the first day for the 15-s condition ($M = -.11$ vs. $M = -.17$), $F(1, 2154) = 4.86$, $p < .05$, with more attribute-based processing under time pressure. In contrast, however, there was no effect of time pressure on pattern of processing in the 25-s condition (M = .15 vs. M = .18), $F(1, 2154) = 1.21$, *ns*. Thus, we find evidence of a shift toward more attribute-based processing under severe time pressure, but no shift in processing with moderate time pressure.[3]

Finally, accuracy (GAIN) was lower under time pressure for both the 15-s (M = .58 vs. M = .43), $F(1, 2154) = 9.22$, $p < .01$, and 25-s conditions (M = .77 vs. M = .66), $F(1, 2154) = 4.95$, $p < .05$. Although not shown in Table 4, the detrimental effect of time pressure on GAIN was again greatest for the first block of trials, particularly for the 15-s condition (M = .29).

Dispersion effects. The pattern of effects for dispersion in probabilities for Experiment 2 was similar to that found for Experiment 1. With respect to amount of processing, for the 15-s condition there was an effect of dispersion on ACQ (M = 35.19 vs. M = 29.67), $F(1, 2154) = 24.54$, $p < .001$, and a marginal effect on TPERACQ (M = .56 vs. M = .55), $F(1, 2154) = 2.77$, $p < .10$. For the 25-s condition, there was an effect on ACQ (M = 40.81 vs. M = 36.46), $F(1, 2154) = 16.41$, $p < .001$, and a marginal effect on TPERACQ (M = .58 vs. M = .57), $F(1, 2154) = 3.52$, $p < .07$.

Analyses of simple effects for the selectivity and filtration measures show effects for the 15-s level on PTMI (M = .31 vs. M = .40), $F(1, 2154) = 134.98$, $p < .001$, PTPROB (M = .25 vs. M = .28), $F(1, 2154) = 7.01$, $p < .01$, VAR-ATTRIB (M = .010 vs. M = .022), $F(1, 2154) = 130.01$, $p < .001$, and VAR-ALTER (M = .010 vs. M = .013), $F(1, 2154) = 14.83$, $p < .001$. For the 25-s group there were effects on PTMI (M = .31 vs. M = .40), $F(1, 2154) = 112.62$, $p < .001$, and VAR-ATTRIB (M = .005 vs. M = .019), $F(1, 2154) = 115.15$, $p < .001$. There was a marginal effect on PTPROB (M = .20 vs. M = .21), $F(1, 2154) = 2.72$, $p < .10$, and a marginal effect on VAR-ALTER (M = .008 vs. M = .010), $F(1, 2154) = 3.20$, $p < .08$. Thus, there is evidence for greater selectivity under high dispersion, but it is stronger for the 15-s condition.

There were also strong effects on PATTERN for both the 15-s (M = −.01 vs. M = −.27), $F(1, 2154) = 82.03$, $p < .001$, and 25-s conditions (M = .31 vs. M = .01), $F(1, 2154) = 91.99$, $p < .001$. Processing becomes more attribute based with higher dispersion. The results for dispersion for the 25-s condition are important in that they demonstrate adaptation to the dispersion manipulation. Hence, the failure to adapt to time pressure via strategy change in the 25-s condition is not due to a total failure to obtain adaptivity in that condition.

There are no effects of dispersion on GAIN in either the 15-s (M = .50 vs. M = .51), $F(1, 2154) = .09$, *ns*, or 25-s conditions (M = .70 vs. M = .71), $F(1, 2154) = .06$, *ns*. Finally, there are significant dispersion by time pressure interactions for ACQ, $F(1, 2154) = 10.36$, $p < .001$, TPERACQ, $F(1, 2154) = 6.04$, $p < .01$, and VAR-ATTRIB, $F(1, 2154) = 10.61$, $p < .001$, for the 15-s condition; for the 25-s condition, the only significant interaction was for ACQ, $F(1, 2154) = 10.80$, $p < .001$.

Once again, the hypothesis of adaptivity in processing was strongly supported for dispersion in probabilities. The subjects in Experiment 2, like those in Experiment 1, were apparently able to take advantage of context changes to reduce processing effort while maintaining essentially the same level of accuracy.

Day and level effects. As noted earlier, the multivariate analysis of variance showed a significant day by level interaction. Subjects who experienced a moderate time constraint on the first day acted differently than did those who faced a severe constraint on the first day. An examination of the results in Table 4 indicates little difference in the processing for Group 2 (25-s time pressure for the first day) between Day 1 and Day 2. The means for both VAR-ATTRIB and PATTERN, for example, are similar for each day. A simple explanation is that a 15-s time constraint on the second day was not that severe a time constraint. Experience with the task on the first day resulted in the constraint of 15 s on the second day being more like a moderate level of time pressure. On the other hand, note that the second-day responses for Group 1 (15-s time pressure for the first day) are intermediate between the first day responses to 15-s time pressure and the first day responses to 25-s time pressure.

Another interesting comparison concerns the no-time-pressure data for Groups 1 and 2 on the first day. Consider, for example, the results for PATTERN. The no-time-pressure mean for the 15-s condition was −.11. The mean for the 25-s condition was .15. Thus, it appears that there was some carryover from behavior generated in response to the time-pressure trials to the no-time-pressure trials. This suggests that the degree of adaptivity to time pressure found in these experiments was not perfect on a trial by trial basis. The development of a strategy appropriate to a particular level of time pressure apparently affected the strategy used in the no-time-pressure situations. There is also evidence for such carryover in the second-day responses of Group 1 discussed earlier.

Discussion

The results of Experiment 2 support the findings of Experiment 1 and show that subjects adapt to changes in context (dispersion) by exhibiting changes in selectivity, type of processing, and amount of processing while maintaining accuracy. Subjects appear to adapt to severe time pressure by acceleration, filtration, and changes in strategy. They do not appear to change strategy in response to more moderate time pressure. The second-day results also demonstrate some interesting effects regarding how adaptation to one choice environment carries over to adaptation to a different choice environment. Table 5 summarizes the main effects for dispersion and time pressure for both experiments.

An Alternative Hypothesis

Although the pattern of results for time pressure for Experiment 2 is consistent with the findings of Experiment 1, an

[3] A third experiment, identical in procedure to Experiment 1 but using a 25-s level of time pressure, was also conducted. The results were similar to those reported in the text. Under 25 s of time pressure there was evidence of acceleration of processing, weak support for the hypothesis of filtration, and no evidence of changes in the pattern of processing. More details on that experiment are available from the authors.

Table 5
Summary of Main Effect Results for Dispersion and Time Pressure: Experiments 1 and 2

Dependent measure	Dispersion			Time pressure		
		Experiment 2			Experiment 2	
	Experiment 1	TP = 15 s	TP = 25 s	Experiment 1	TP = 15 s	TP = 25 s
ACQ	−***	−***	−***	−***	−***	−***
TPERACQ	−***	−*	−*	−***	−***	−***
PTMI	+***	+***	+***	+***	+***	+**
PTPROB	*ns*	+***	+*	+***	+***	+*
VAR-ALTER	+**	+***	+*	*ns*	*ns*	*ns*
VAR-ATTRIB	+***	+***	+***	+**	+***	+*
PATTERN	−***	−***	−***	−*	−**	*ns*
GAIN	*ns*	*ns*	*ns*	−***	−***	−**

Note. The signs represent the direction of each effect (e.g., higher dispersion led to fewer acquisitions in Experiment 1). TP = time pressure. ACQ = number of information boxes examined. TPERACQ = time per information acquisition. PTMI = proportion of time on the most important attribute. PTPROB = proportion of time on the probability information. 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). PATTERN = index reflecting relative amount of attribute-based (−) and alternative-based (+) processing. GAIN = relative accuracy of choices.
* p < .10
** p < .05
*** p < .01

alternative explanation, suggested by an anonymous reviewer, must be examined. Suppose subjects only adjust to the dispersion manipulation. They might do this by first examining the probabilities and then engaging in a mixture of attribute- and alternative-based processing under low dispersion or mostly attribute-based processing if dispersion is high. If one supposes further that whatever alternative-based processing is used tends to be greater toward the end of the choice process, then a simple truncation of the process under time pressure could lead to the observed results. Subjects may not change their processing strategy but may simply use a truncated version of the strategy under time pressure. This possibility must be seriously considered, as prior research (e.g., Bettman & Park, 1980) has shown that alternative-based processing does increase relative to attribute-based processing later in the choice process.

To examine this alternative hypothesis, we consider processing patterns early in the choice process. In particular, we consider the processing occurring in the first eight acquisitions of each time pressure trial. Eight acquisitions were selected at the unit of analysis for several reasons. First, two distinct processing patterns could be exhibited within eight acquisitions, namely, examination of all four probabilities and all four values for one alternative or acquiring information on all four probabilities and all four values for one attribute across alternatives. Although subjects may not follow these two patterns in pure form, eight acquisitions should allow for any differential tendencies in starting the process to emerge. Second, eight acquisitions is also roughly half the average number of acquisitions for the 15-s time pressure condition. Over 98% of the trials had eight acquisitions or more.

The alternative hypothesis can be tested by comparing the processing patterns for these first eight acquisitions for each time pressure trial for the 15-s and 25-s time pressure conditions. If the alternative truncation hypothesis is correct, there should be no difference between the 15-s and 25-s conditions on these initial acquisitions for the time pressure trials, as the overall differences between these conditions are hypothesized to be due to truncation at the end of the process. If our interpretation that subjects are using different strategies is correct, however, there should be differences between the 15-s and 25-s conditions at the beginning of the process.

We analyzed the data for the first eight acquisitions for each time pressure trial from Experiment 2. The variables examined were two selectivity measures, the variances in the proportion of time spent on attributes (VAR-ATTRIB) and alternatives (VAR-ALTER); and the relative proportion of alternative- and attribute-based processing (PATTERN). These variables were selected because they should provide sensitive indices of the early processing pattern. We have hypothesized that subjects under severe time pressure should try to do a quick evaluation of as many alternatives as possible on a limited number of attributes. This pattern should *not* characterize subjects with 25-s time pressure if our hypothesis that strategy change occurs only under severe time pressure is correct. That implies more attribute-based processing and greater variation in processing across attributes for the 15-s condition. Because only the first few acquisitions are examined, this should also imply *less* variation across alternatives for the 15-s condition, because subjects will not have had time to eliminate alternatives. Rather, they may be doing an initial screening, with the values of all alternatives examined for the attribute or attributes considered. Thus, the strategy change hypothesis predicts the foregoing differences between the 15-s and 25-s conditions for the eight initial acquisitions per time pressure trial, whereas a strict truncation hypothesis should predict no differences.

The results support the strategy change hypothesis and are not consistent with the truncation hypothesis. VAR-ATTRIB is marginally greater for the 15-s condition than the 25-s condition (M = .033 vs. M = .026), $F(1, 526) = 2.84$, $p < .10$, and VAR-ALTER is significantly less for the 15-s condition (M = .075 vs. M = .105), $F(1, 510) = 7.03$, $p < .02$. The tendency for the 15-s condition to engage in more attribute-based processing (more negative values of PATTERN) is also marginally significant ($M = -.33$ vs. $M = .01$), $F(1, 474) = 3.35$, $p < .08$. Although these results do not all reach conventional .05 levels of significance, they are all directionally consistent with the strategy change hypothesis rather than truncation. In addition, there were no significant differences on these variables for the no-time-pressure trials between the 15-s and 25-s conditions, $F(1, 526) = 1.31$, $F(1, 473) = .18$, and $F(1, 382) = .59$ for VAR-ATTRIB, VAR-ALTER, and PATTERN, respectively. This supports the notion that different strategies are adaptive responses to different levels of time pressure, not a general tendency of the different subject groups.

To provide further insights into the pattern of processing over the course of a decision, the responses of subjects were compared for the first eight acquisitions and last eight acquisitions of all trials on PATTERN and PTPROB. Consistent with prior research (Bettman & Park, 1980), there was more attribute-based processing for the earlier acquisitions than for the later acquisitions, both for the 15-s condition ($M = -.35$ vs. $-.05$), $F(1, 1137) = 46.86$, $p < .001$, and the 25-s condition ($M = -.08$ vs. .26), $F(1, 873) = 51.94$, $p < .001$. There was also a greater initial focus on probabilities for both the 15-s ($M = .57$ vs. $M = .11$), $F(1, 1264) = 1837.04$, $p < .001$, and 25-s conditions ($M = .58$ vs. $M = .08$), $F(1, 944) = 2576.23$, $p < .001$. The PTPROB means were essentially the same for both the 15-s and 25-s conditions. Thus, the 15-s and 25-s conditions exhibit different responses to time pressure from the beginning. Even though processing becomes relatively more alternative based over the course of a trial, the difference between the two conditions remains.

General Discussion

Previous research has shown that the same individual will often use diverse strategies to make a decision, contingent on task demands (Payne, 1982). A major problem for current cognitive research is to be able to better understand and predict when a particular strategy will be used.

This article has examined effort and accuracy considerations in the selection of strategies for making a choice. The general hypothesis is that selection among strategies is adaptive, in 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 article first outlined an approach to modeling the impact of task and context variables on decision strategies by using elementary information processes to measure effort and computer simulation models to examine accuracy and effort trade-offs. A Monte-Carlo simulation examined the impact of variation in the presence or absence of time pressure, dispersion in probabilities, presence or absence of dominated alternatives, and different problem sizes on the accuracy and effort of a variety of choice heuristics. Strategies were identified that 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 use a variety of heuristics adaptively. Of particular interest was the finding that under time constraints, several attribute-based heuristics (e.g., EBA and LEX) were more accurate than a normative procedure such as expected value maximization, because that procedure had to be truncated when it ran out of time.

The simulation does not really answer the question of how a strategy is selected, however. The implicit viewpoint in our work is that a decision maker possesses a repertoire of well-defined strategies and selects among them when faced with a decision by considering the expected costs and expected benefits of each strategy. This top-down view of strategy selection is consistent with previous models like that of Beach and Mitchell (1978). Alternatively, strategies may develop during the course of solving a decision problem in a more bottom-up, constructive, and ad hoc fashion (Bettman, 1979). Throughout a choice episode a decision maker will be alert to structure in the choice set that can be exploited to reduce effort and perhaps increase accuracy. Regardless of how strategy selection is controlled, the simulation results do suggest how certain context and task variables affect the relative effort and accuracy of possible strategies.

Adaptivity to Decision Environments

Experiments 1 and 2 tested the degree of correspondence between the efficient processing strategies for a given decision problem identified by the simulations and the actual information processing behavior exhibited by people. The results for actual decision behavior tended to validate the patterns predicted by the simulation.

More specifically, subjects generally acquired less information, spent less time per acquisition, spent proportionately more time on the most important attribute, displayed greater variance in the proportion of time spent on the various alternatives and attributes, and used more attribute-based processing when dispersion in the weights (probabilities), a context variable, was high rather than low. The effects of dispersion on the proportion of time spent on probabilities were not consistent across studies, although more time was spent on probabilities under high dispersion in the majority of cases. Such adaptivity in strategy usage in response to a context variable demonstrates that people are sensitive to a change in the task environment that potentially impacts the relative accuracy of heuristics as well as affecting relative effort.

In addition, several effects of time pressure were demonstrated. Under moderate time pressure, subjects were shown to accelerate their processing. There was some evidence, although weaker, that subjects selectively 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 information processing strategies. There was more attribute-based processing and more variance in the proportion of time spent on various attributes as time pressure increased. Counter to predictions, there were not systematic effects of time pressure on the variance in the proportion of time spent on various alternatives, implying that subjects were equally consistent in the proportion of information searched across alternatives, regardless of time pressure. One possible explanation is that the nature of the display may have made complete scans of an attribute relatively easy.

Across the two experiments, the relative amount of dimensional processing (PATTERN) was an average of 41% greater under time pressure of 15 s compared with no time pressure. In contrast, the relative amount of dimensional processing was 20% less under time pressure of 25 s compared with no time pressure. The variance in processing across attributes (VAR-ATTRIB) was increased by 40% on average for the 15-s time pressure conditions versus no time pressure; however, the average increase was 21% for the 25-s time-pressure conditions.

There are several important aspects of these time-pressure results. First, they provide a strong demonstration of the adaptivity of processing strategies to time pressure. Second, the results of the experiments imply that there may be a hierarchy of responses to time pressure. People may first attempt to simply accelerate their processing and 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. Of course, the specific strategies found in our studies may be a function of the problem format used. Different adaptive strategies would presumably be found for different task structures.

Learning Effort–Accuracy Trade-offs

The evidence for processing changes reported in the present experiments suggests that people were learning to adapt their behavior to changes in task and context. Yet none of the experiments provided the subjects with explicit accuracy or outcome feedback. Johnson and Payne (1985) argued that a decision maker has access to a fairly rich data base about the course of his or her own decision processes. They hypothesize that this *process feedback* could provide the information necessary for strategy change. For example, a decision maker might induce the LEX rule by first noticing that certain outcomes seem much more probable than others (Klein, 1983, reports data supporting this kind of learning about the task). Next, the decision maker might evaluate a strategy that takes advantage of the features of the task by checking whether the outcomes are consistent with several simple principles of choice. For instance, the decision maker might check that the new strategy does not select dominated alternatives, and that it selects alternatives that have satisfactory levels of other outcomes.

General knowledge of what makes for a good decision process may also play a role in learning to adapt. For instance, the idea that a good decision requires considering all relevant information is likely to be held by many people, as is the notion that a good process will examine the most important information.[4] Consequently, when faced with a decision task in which it is impossible or very difficult to process all information, the decision maker might use the information he or she has gained about the task to decide what information is less important and can be ignored. An example of such task information is that some probabilities are much smaller than others under high-dispersion conditions.

The data presented in this article demonstrate that people shift decision strategies in response to a context change in ways that maintain accuracy, without explicit outcome feedback. Reder (1987) has also found evidence of strategy changes in a question answering task without outcome feedback. She suggests several ideas regarding the mechanisms of adaptive strategy selection, such as a "feeling-of-knowing" process, that may relate to the "level of confidence" discussed by Busemeyer (1985). People may seek to develop strategies that take advantage of problem structure so as to minimize effort while maintaining a feeling of knowing or desired level of confidence that they are making a reasonable decision.

The present results, taken as a whole, provide strong evidence for adaptivity in decision making, although the degree of adaptivity was not perfect. There did appear to be some carry-over effects in terms of processing strategies from trial to trial and from day to day. Despite these carry-over effects, however, individuals did change information processing strategies depending upon the changing structure of the choice environment from problem to problem. This variability in processing 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. It is likely that certain environmental properties may be more easily noticed, and hence more adapted to, than others. For example, it may be difficult for people to notice attribute intercorrelations (Crocker, 1981).

Finally, 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 lead to violations of certain principles of rationality (Tversky, 1969). The use of heuristic processes that lead to decision errors may reflect a trade-off 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 change processing strategies in ways that are appropriate given somewhat subtle changes in the structure of the decision problems they face.

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[4] As part of the debriefing process for Experiment 2, subjects were asked what strategy they would advocate to identify the "best" choice under no time pressure. The use of all information, including a weighting of payoffs by probabilities, was identified by many of the subjects. For time pressure, the subjects indicated that use of as much of the most important information as possible was a major consideration.

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