

## Correlation, Conflict, and Choice

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We examined the degree to which individuals adapt their decision processes to the degree of interattribute correlation and conflict characterizing a decision problem. On the basis of an effort-accuracy framework for adaptive decision making, we predicted that the more negatively correlated the attribute structure, the more people will use strategies that process much of the relevant information and make trade-offs. A computer simulation study supported these predictions, and two experiments using process-tracing techniques to monitor information acquisition indicated that individuals did indeed respond to interattribute correlation by shifting their processing strategies in ways that are adaptive according to the effort-accuracy framework. In particular, they faced conflict rather than avoided it and generally processed more information, were less selective, and showed more alternative-based processing in negatively correlated environments.

One of the most robust findings in research on decision making is that the same individual often uses diverse strategies to make a decision, contingent on task demands (Einhorn & Hogarth, 1981; Payne, Bettman, & Johnson, 1992). Sometimes people attempt to (a) use all of the relevant information and (b) make trade-offs among the good and bad aspects of each alternative. These processes are important components of normative prescriptions for choice, of which the most common is the weighted additive decision rule. Rules using such processes are "conflict confronting" (i.e., compensatory) because differences in values are faced and resolved by compromise (Einhorn & Hogarth, 1981). Because rules that make trade-offs weight these differences, they reflect a quantitative approach to choice (Tversky, Satath, & Slovic, 1988).

At other times, people adopt more qualitative and non-compensatory heuristic strategies that simplify the decision problem by ignoring potentially relevant problem information, by avoiding direct trade-offs among values, or both. Examples of such heuristic decision strategies are elimination by aspects (Tversky, 1972) and "satisficing" (Simon, 1955). Although these heuristics may produce errors in decision, such as violations of transitivity (Tversky, 1969), they also have potential advantages. First, heuristic strategies save cognitive effort, allowing people with limited information-processing capabilities to deal with complex decision environments (Simon, 1955). Second, as Hogarth (1987) argued, noncompensatory heuristics are conflict avoiding and allow the decisionmaker to avoid the conflict-laden and emotionally difficult questions associated with some trade-offs (e.g., how much extra one is willing to pay for a car in order to reduce the chances of an accident).

Given that the use of strategies is highly contingent, how adaptive are people in selecting a particular strategy to solve a particular decision problem? That is, are people intelligent, if not normative, processors of information across various decision environments? In earlier work, we proposed a framework to address these questions (Payne, Bettman, & Johnson, 1988, 1993). We argued that people select decision strategies by trading off the costs (primarily effort) and the benefits (primarily accuracy) associated with different strategies in a given environment. Thus, we believe that strategy selection in decision making is both intelligent and adaptive even though heuristic strategies, which may lead to decision error, are often used. We have found substantial support for this effort-accuracy approach to strategy selection (Payne et al., 1993). For example, we have shown that in environments characterized by varying degrees of time pressure, subjects switch decision strategies in a manner that reflects the fact that the potential accuracy of a decision strategy varies with the amount of time available to complete the decision (Payne et al., 1988).

Task and context variables are properties of the decision environment that influence selections among various decision strategies. Task variables reflect general characteristics of the decision problem (e.g., the number of alternatives, response mode, and time constraints) that are not dependent on the particular values of the alternatives. Task variables generally have their greatest impact on the relative effort needed to execute various decision strategies, although the accuracy of the choice can also be affected (Johnson & Payne, 1985). There is much evidence showing contingent strategy use as a function of task variables (Payne et al., 1992). Context variables, on the other hand, reflect the particular values of the alternatives and include factors such as the presence or absence of dominated alternatives (alternatives that are worse than some other option on all attributes) and the similarity among the alternatives. Although context variables affect both the effort and accuracy of choice strategies, their greatest impact seems to be on the relative accuracy of strategies (Johnson & Payne, 1985). The evidence for contingent processing as a func-

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tion of context variables is less extensive than that for task variables (Payne et al., 1992).

In this article we describe the investigation of the adaptivity of decision processing to a context variable that is particularly interesting for theoretical reasons: the intercorrelations among the attribute values defining the choice alternatives. The intercorrelations among attribute values reflect the extent to which one has to give up something of value in order to get something else of value.

### Correlation and Strategy Selection

We were interested in the intercorrelational structure of a choice problem for several reasons. One reason is that several authors have suggested that people should use heuristic strategies less often in negatively correlated environments and instead use strategies that examine all of the relevant information and make trade-offs, such as weighted adding. This suggestion is based on the argument that heuristic decision strategies are relatively less accurate when attributes are negatively correlated (Einhorn, Kleinmuntz, & Kleinmuntz, 1979; Newman, 1977). Because of this loss in accuracy, if the cognitive costs (in terms of computations) associated with various strategies are unaffected by correlation structures, an effort-accuracy framework predicts that heuristic strategies will be less attractive in negatively correlated environments.<sup>1</sup>

The intercorrelational structure is also conceptually interesting because negative correlation increases the conflict associated with the choice set; that is, selecting one alternative means that one has to give up something of value to obtain something else of value (Einhorn & Hogarth, 1981). Because one could argue that people seek to avoid confronting conflict-laden decision problems (Hogarth, 1987; Shepard, 1964), people may adopt heuristic strategies that avoid explicit trade-offs when faced with negatively correlated choice sets. The lexicographic strategy, which picks the alternative that is best on the most important attribute, is a good example of a decision strategy that avoids trade-offs (Tversky, 1969). Thus, the accuracy-effort and conflict-avoidance approaches make opposing predictions about the relative frequency of use of heuristics that avoid trade-offs and strategies that make trade-offs in negatively correlated decision environments.

Another reason that correlation among attributes is of interest is that decisionmakers may not notice or accurately estimate the degree of correlation in a choice set. There is substantial evidence that people can be poor judges of the degree of correlation between variables (Alloy & Tabachnik, 1984; Crocker, 1981). Therefore, people may fail to adapt to correlation because they are unable to judge such correlations accurately. Hence, it is also possible that the relative use of heuristic strategies would be unaffected by the level of interattribute correlation.

To summarize, we have identified three competing hypotheses concerning the effects of the correlational structure of a decision environment on strategy selection: (a) An effort-accuracy perspective on strategy selection leads to the hypothesis that the more negatively correlated the attribute structure, the more people will attempt to use strategies that

process all relevant information and make trade-offs. (b) A perspective that emphasizes the avoidance of conflict in decisions leads to the opposite hypothesis that the more negatively correlated the attribute structure, the more people will use heuristics that selectively acquire information and avoid trade-offs. (c) The research on judgment of covariation leads to the hypothesis that variations in correlation structure may have no effect on the type of decision strategy used.

Prior research does not provide clear support for any of these competing hypotheses. Klein and Yadav (1989), for example, found that the number of dominated alternatives in a choice set affected the accuracy of and the time required to make a decision: The fewer dominated alternatives present (and hence the more negative the correlation structure in general), the less accurate and the more time demanding the decision. However, Klein and Yadav also found that people were poor judges of the level of correlation among the attributes when their only information consisted of specific choice alternatives.

In a more direct test of correlational structures, Huber and Klein (1991) found that the more negative the environmental correlation, the less severe the cutoffs used to screen alternatives, implying more complete processing of the information about all of the available options. Huber and Klein (1991) reported, however, that correlation structure had an effect on cutoff severity only when subjects were given an explicit statement about the correlation among attributes. When the correlation structure was manipulated only by providing the values of the choice alternatives, without an explicit statement, cutoff severity was not significantly different in positive and negative correlation environments. Thus, it is not clear from these results how adaptive people would be to correlational structures that must be inferred from the choice problem itself. In addition, the studies by Huber and Klein and by Klein and Yadav (1989) did not directly examine process-level measures of the type of choice processing carried out.

Perhaps the most direct tests of strategy shifts as a function of correlational structure were done by Johnson, Meyer, and Ghose (1989). Using a process-tracing method based on the monitoring of information acquisition behavior, they found no evidence of any shift in processing in response to correlational changes. However, they manipulated both correlation and the number of available alternatives. It is possible that adaptation to the number of alternatives, a noticeable task variable, interfered with adaptation to the less noticeable correlational context variable. In addition, subjects were

<sup>1</sup> Another general effect of negative correlation is to reduce the differences among the alternatives in terms of overall value. Thus, negative correlation structures generally decrease the difference in value achieved from choice of the first versus the second best alternative. Therefore, one could argue that under negative correlation, the use of heuristics (effort-saving strategies) becomes more attractive because the size of an error is smaller even though the chance of an error is greater. It appears, however, that people process more information, not less, when the attractiveness difference between alternatives is small (Brockenholt, Albert, Aschenbrenner, & Schmalhofer, 1991).

given only a limited number of decision problems in each condition of the study. Subjects may be more inclined to adapt to subtle context variables such as correlation when given experience over many trials in environments in which task variables do not also vary.

As indicated earlier, there remains much doubt about whether, and how, people adapt their decision strategies to variations in the correlational structure of the decision environment. Therefore, the purpose of our research was to investigate the degree to which individuals would adapt to different correlational structures by changing the way they process information. Consistent with our effort-accuracy perspective, we hypothesized that the more negatively correlated the attribute structure, the more people will attempt to use much of the relevant information and make trade-offs, as the weighted adding strategy would do. In order to encourage adaptation to the subtle context variable of correlation, we had subjects make choices over several trials and paired correlation with a second context variable (Experiment 1) and presented correlation with no other environmental variable (Experiment 2).

The remainder of this article is organized as follows: First, a computer simulation study is briefly reported that allowed us to make the predictions of our effort-accuracy framework more concrete. The accuracy and effort levels for various choice strategies were evaluated for several correlational structures. These simulation results were then used to predict how decisionmakers might change several specific aspects characterizing their information processing across different levels of correlation. Next, two experiments are reported that tested the extent to which actual decision behavior in different correlational environments reflects these predicted changes in aspects of processing. We conclude with a discussion of strategy implementation and when adaptivity in strategy selection might fail.

#### A Monte Carlo Simulation of Effort and Accuracy in Environments With Differing Levels of Interattribute Correlation

The simulation studies to be reported enabled us to make predictions about the patterns of processing that would be exhibited in various task environments by idealized, adaptive decisionmakers attending to both accuracy and effort in selecting a decision strategy. More specifically, the simulations examined the performance of several choice strategies across different choice environments. In all cases, the alternatives were gambles with outcomes (attributes of value or, for convenience, attributes) that had different payoffs but the same probability for each alternative. In other words, each of the alternatives might have had a different value for a given outcome, but the probability of receiving that outcome was the same for all alternatives. The different choice environments also varied with respect to the level of interattribute correlation and the degree of dispersion of probabilities in each set of gambles.

We used such choice problems for two reasons. First, it was easy to tie real consequences to choices among gambles, for

instance, by allowing subjects to actually play a selected gamble for real money. Second, using such gambles allowed us to focus on expected value maximization as a criterion for accuracy, as discussed shortly.<sup>2</sup>

#### Choice Strategies

We used seven decision strategies in the simulation: weighted adding (WADD [expected value maximization]), lexicographic (LEX), elimination by aspects (EBA), equal-weighted adding (EQW), majority of confirming dimensions (MCD), satisficing (SAT), and a random choice rule (RAND). The WADD rule is the most information intensive, using all of the values for each alternative on all of the outcomes and all of the probabilities. WADD was the only "normative" decision strategy considered in the simulation: If executed correctly, the WADD strategy will always yield a choice consisting of the alternative with the highest expected value in the decision set. The RAND rule, on the other hand, uses none of the available information and represents a minimum baseline for measuring accuracy and effort. For further details on these rules, see Payne et al. (1988).

In solving risky choice problems, the decisionmaker must search among probabilities and the values associated with the outcomes for each alternative. The different decision strategies just outlined can be thought of as different rules for conducting that search and can vary in a number of aspects (see Bettman, 1979). One of the most important distinctions among rules is the extent of compensatory (i.e., making trade-offs) as compared with noncompensatory processing. A related aspect is the degree to which the amount of processing is consistent (as opposed to 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).<sup>3</sup> A more variable (selective) processing pattern indicates 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. Regardless of whether processing is consistent, the total amount of information examined can vary from cursory to exhaustive.

<sup>2</sup> Assessing accuracy in preferential choice tasks without specified attribute weights and when preferences vary across individuals is more problematic (e.g., Meyer & Johnson, 1989).

<sup>3</sup> Bockenholt, Albert, Aschenbrenner, and Schmalhofer (1991) argued that this assumption is not always correct if the decisionmaker uses a criterion-dependent pairwise choice process (i.e., a decision process for deciding between two alternatives in which comparisons between the two alternatives are made on each attribute in turn, and an alternative is chosen when enough evidence in favor of that alternative has accrued to surpass a criterion). However, given larger sets of alternatives (i.e.,  $N > 2$ ), the assumption made here is more likely.

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. By 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 Doshier (1983) suggested that attribute-based processing is cognitively easier.

The various strategies simulated represent different combinations of these aspects. The WADD strategy uses consistent and alternative-based processing and examines all available information. The EQW strategy uses consistent and alternative-based processing but uses a subset of the available information (weights are ignored). 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 LEX strategy is also selective and attribute based, and the SAT strategy is selective and alternative based. The total amount of information processed is also contingent on the particular values of the alternatives for these latter two strategies. We used the simulation results to make predictions about how these aspects of processing might change across various levels of interattribute correlation.

Note that these general aspects of processing can be used to characterize the general approaches to choice we considered earlier in environments characterized by negative correlation. For example, conflict-confronting strategies that make trade-offs will involve a more total information search, are less selective in terms of information considered, and are more alternative based. The more heuristic, conflict-avoiding strategies, on the other hand, should use less information, be more selective, and be more attribute based.

### Measuring Accuracy and Effort

The accuracy of choice can be measured in many ways (e.g., not selecting dominated alternatives or not displaying intransitive preferences); however, we focused on expected value (EV) maximization as a normative rule for risky choice. In particular, we used a relative measure of accuracy that compares the relative performance of a particular heuristic to the two baseline strategies: WADD and random choice. The measure is defined by the following equation:

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

For each choice set, the maximum EV possible and the EV associated with a random selection were determined. The EV of the alternative selected by the decision heuristic was then compared with these two baseline values. This relative accuracy measure was bounded by a value of 1.00 for the EV

rule and an EV of 0.0 for random selection. It provides a measure of the relative improvement of a heuristic strategy over random choice. For further discussion of the measure, see Johnson and Payne (1985) and Payne et al. (1988). We examine the robustness of our results under other possible accuracy measures shortly.

Each of the choice heuristics listed earlier can also be characterized in terms of operators, or elementary information processes (EIPs). The set of EIPs we have found useful includes (a) *reading* an alternative's value on an attribute into short-term memory; (b) *comparing* two alternatives on an attribute; (c) *adding* two values in short-term memory; (d) calculating the size of a *difference*; (e) weighting one value by another (*product*); (f) *eliminating* an alternative or outcome from consideration; (g) *moving* to the next element in the external environment; and (h) *choosing* the preferred alternative. These EIPs provide a common language for describing diverse decision strategies (Johnson & Payne, 1985).

Each of these strategies was operationalized as a production system model. The productions specify a set of actions (EIPs) and the conditions under which they occur. The effort required by a particular strategy in a particular choice environment is measured by a count of the total number of EIPs required by the production system model for the strategy to reach a decision in that environment.<sup>4</sup> Each of the production systems was unique for its strategy, and all were designed to minimize the number of operations. Because decisionmakers may not necessarily do this, our implementations represent minimum estimates of the effort required to use each strategy.

In reporting the following results, we transformed the total effort count to a relative effort-savings measure. This measure was obtained by dividing the effort count for a given heuristic by the effort count for the most effortful rule: WADD. This figure was then subtracted from one. This yielded a proportion of effort savings relative to the WADD rule.

### The Task Environment

The task environment studied matched that used in the experiments reported later with respect to the number of alternatives available and the number of attributes (outcomes) describing the alternatives. Choice sets with four alternatives and four attributes were used.

Two context variables were also varied. One context variable, the degree of intercorrelation among the attributes, was varied at two levels: (a) sets with an average positive intercorrelation of .6 among pairs of attributes and (b) sets with a maximum average negative rank order correlation between

<sup>4</sup> Using a count of the total number of elementary information processes (EIPs) assumes that each EIP requires the same level of effort. That assumption can be relaxed by weighting different EIPs to reflect differing effort levels (see Bettman, Johnson, & Payne, 1990). Because the results are essentially the same if weights are used, we focus on the simpler counts of EIPs throughout this article.

all pairs of attributes; this is in general equal to  $[-1/(n-1)]$ , where  $n$  is the number of attributes (see Green & Krieger, 1986). We chose these two levels of correlation because the contrast provides for the clearest hypotheses about strategy differences.

A second context variable, the degree of dispersion of probabilities within each gamble, was also varied at two levels: low and high. To illustrate, a four-outcome gamble with a low degree of dispersion might have probabilities of .18, .25, .28, and .29 for the four outcomes, respectively. On the other hand, a gamble with a high degree of dispersion might have probabilities of .21, .55, .15, and .09 for the four outcomes. This variable was included because prior research has shown that it is a context variable that influences the effectiveness of heuristics, and it is also a variable that people adapt to behaviorally (see Payne et al., 1988). Including both context variables allowed us to investigate how the impact of correlational structure on the performance of choice heuristics might be affected by another context variable of importance. In addition, using these two context variables may help us to interpret the results of our experiments. For example, it would be interesting to see whether people failed to adapt to correlational structure but adapted to a more easily detected context variable such as the dispersion in probabilities.

### Procedure

Each of the decision rules was applied to 1,000 decision problems generated to match the conditions specified for each of the four cells defined by a 2 (levels of interattribute correlation)  $\times$  2 (low or high dispersion of probabilities) factorial.<sup>5</sup> The IMSL STAT/LIBRARY subroutine RNMVN, which generates multivariate normal random variates, was used to generate the differing levels of interattribute correlation (ISML, 1987, pp. 1033–1034). For each problem, the alternative selected and the count of elementary operations used by each rule was recorded. The EV for the alternative selected was then used to generate the relative accuracy score.

### Results

Table 1 shows the average values of relative accuracy and relative effort savings for problems of size  $4 \times 4$ , the two levels of correlation, and the two levels of dispersion. Two aspects characterizing each strategy, whether it used information selectively and was alternative based or attribute based, were included to aid in the interpretation of the results.

The most striking characteristic of the results is that heuristic decision strategies were generally less accurate in the environment with negative interattribute correlations than in the positively correlated environment. For example, performance for the MCD, EQW, and SAT rules fell precipitously in the negative environment. From average levels of .72 and .68 in positive correlation, low and high dispersion, MCD fell to .05 and  $-.04$ ; EQW fell from .94 and .87 to .30 and .19; and SAT fell from .48 and .47 to .03 and  $-.01$  in negative

correlation, low and high dispersion. Some heuristics maintained relatively good performance levels in both positive and negative environments, however, particularly LEX and EBA. However, the *gap* between the performance of the best heuristic and that of the WADD rule was still larger for negative than for positive correlation, especially under low dispersion; the gap was .40 for negative correlation, low dispersion versus .06 for positive correlation, low dispersion and .20 for negative correlation high dispersion versus .13 for positive correlation, high dispersion. The results also show that the level of dispersion had a greater impact under negative correlation than under positive correlation.

Given these results, the simulation suggested that individuals would need to devote the effort to use WADD to obtain the highest levels of accuracy under negative correlation. Thus, our simulation results provide support for the belief stated by Einhorn et al. (1979) that heuristic strategies generally are less accurate in negatively correlated environments. In the next section, we consider the robustness of these results under different specifications for accuracy.

### *Robustness of the Simulation Results for Different Accuracy Criteria*

Before summarizing the implications of our simulation work for our experiments, we examine the robustness of the simulation results under alternative accuracy criteria. We used EV as our criterion. Other possible normative criteria exist, however, most notably expected utility (EU) maximization. In EU models, a measure of the utility of an outcome is substituted for the value of the outcome itself. We consider two models of utility (let  $x$  represent the value of an outcome): (a) a power utility function,  $u = x^{2/3}$  (Kahneman & Tversky, 1982) and (b) a negative exponential utility function with constant risk aversion,  $u = 100(1 - e^{-x/100})$ . Both of these utility functions are characterized by risk aversion, the negative exponential to a greater degree than the power function, as opposed to the risk neutrality characterizing the EV strategy.

We ran simulations using these two criteria for four-alternative, four-attribute problems for negative and positive correlation under low and high dispersion. We assumed that whatever the subjective valuation of an outcome's value (i.e., a utility or the value itself), the same amount of effort would be used. Therefore, the various heuristics were characterized by the same relative effort savings, as shown in Table 1; the relative accuracy scores for EV and the two definitions of EU are shown in Table 2.

Although there were some differences across criteria, the results generally agree. When the relative accuracy scores for all four correlation and dispersion conditions for the various rules (including random choice) were rank correlated using Spearman's rho, the correlations were .99 for EV and the

<sup>5</sup> On the basis of prior work (Payne, Bettman, & Johnson, 1988), cutoff levels for the elimination by aspects and satisficing rules were set at their most efficient values for the simulation.

Table 1  
Simulation Results for Accuracy and Effort of Heuristics

Strategy	Processing form	Processing selectivity	Task environment			
			Negative correlation		Positive correlation	
			Low dispersion	High dispersion	Low dispersion	High dispersion
WADD	Alternative	No				
RA			1.0	1.0	1.0	1.0
RES			.0	.0	.0	.0
EQW	Alternative	No				
RA			.30	.19	.94	.87
RES			.50	.50	.50	.50
LEX	Attribute	Yes				
RA			.60	.80	.78	.86
RES			.64	.64	.64	.64
EBA	Attribute	Yes				
RA			.59	.63	.79	.77
RES			.50	.51	.44	.45
MCD	Attribute	No				
RA			.05	-.04	.72	.68
RES			.36	.36	.27	.27
SAT	Alternative	Yes				
RA			.03	-.01	.48	.47
RES			.79	.80	.81	.81

Note. RA = relative accuracy; RES = relative effort savings; WADD = weighted adding strategy; EQW = equal-weighted adding strategy; LEX = lexicographic strategy; EBA = elimination-by-aspects strategy; MCD = majority of confirming dimensions strategy; SAT = satisficing strategy.

power utility function, .77 for EV and the negative exponential utility function, and .82 for the power and negative exponential functions. Thus, the EV and power function cases were highly similar, with the negative exponential results being somewhat more distinct.

Although the performance rankings of individual heuristics may vary somewhat across criteria, note that the gap between the performance of the best heuristic and that of the WADD rule was still larger for negative than for positive correlations in all cases, especially for low dispersion. The gaps for the power utility function were .38 for negative correlation, low dispersion versus .05 for positive correlation, low dispersion and .23 for negative correlation, high dispersion versus .12 for positive correlation, high dispersion. The gaps for the negative exponential utility function were .71 for negative correlation, low dispersion versus .06 for positive correlation, low dispersion and .41 for negative correlation, high dispersion versus .08 for positive correlation, high dispersion. Thus, even under these alternative specifications of accuracy, the best heuristics are generally less accurate in negatively correlated environments, especially under low dispersion.

Note that all of these criteria (EV and the two utility functions) have similar processing implications; that is, all three are characterized by consideration of all information and alternative-based processing. There is additional evidence that subjects associate such processing characteristics with greater accuracy. First, as reported in Payne et al. (1988, p. 551), 13 subjects were asked during debriefing what strategy they would advocate to identify their most preferred choice. Seven of the 13 subjects identified the use of all information

and weighting of payoffs by probabilities. Second, Creyer, Bettman, and Payne (1990) asked subjects to focus on maximizing accuracy for some trials. Subjects examined more information, were less selective, were more alternative based, and were more accurate in those trials. Therefore, when subjects were asked to be more accurate, they responded in ways consistent with use of a WADD rule. We believe that these results demonstrate that our simulation-based predictions are robust for different criteria and that there is independent evidence that subjects believe that WADD models will help ensure accuracy.

Thus, to summarize our simulation results, we found that the gap between the performance level of the WADD rule and the performance level of even the best-performing heuristics widened under negative correlation, especially under low dispersion. This implies that heuristic strategies in general are less attractive under negative correlation; the corollary of this statement is that the WADD strategy, which processes all relevant information and makes trade-offs, is more attractive. Therefore, we expect more use of WADD in the negative correlation conditions, particularly under low dispersion, and less use of heuristics in general under negative correlation.

These simulation results highlight what an idealized, adaptive decisionmaker might do to shift strategies as correlation changes, and these results have been presented in terms of particular strategies. Our experimental work, described later, did not directly observe strategies such as WADD or LEX. However, we view the strategies used in the simulation as prototypical strategies that can be used to hypothesize how aspects of processing may change. Our experimental methodology allowed us to measure several aspects of the strat-

Table 2  
Simulation Results for Alternative Relative Accuracy Measures

Strategy	Task environment			
	Negative correlation		Positive correlation	
	Low dispersion	High dispersion	Low dispersion	High dispersion
WADD				
EV	1.00	1.00	1.00	1.00
EU-Power	1.00	1.00	1.00	1.00
EU-Expon	1.00	1.00	1.00	1.00
EQW				
EV	.30	.19	.94	.87
EU-Power	.22	.16	.95	.88
EU-Expon	-.25	-.15	.94	.92
LEX				
EV	.60	.80	.78	.86
EU-Power	.52	.77	.77	.86
EU-Expon	-.06	.29	.71	.80
EBA				
EV	.59	.63	.79	.77
EU-Power	.62	.67	.80	.78
EU-Expon	.29	.59	.85	.87
MCD				
EV	.05	-.04	.72	.68
EU-Power	.01	-.06	.71	.68
EU-Expon	-.22	-.28	.49	.69
SAT				
EV	.03	-.01	.48	.47
EU-Power	.03	-.01	.49	.47
EU-Expon	.04	-.02	.52	.53

Note. EV = expected value; EU-Power = power function expected utility; EU-Expon = negative exponential expected utility; WADD = weighted adding strategy; EQW = equal-weighted adding strategy; LEX = lexicographic strategy; EBA = elimination-by-aspects strategy; MCD = majority of conforming dimensions strategy; SAT = satisficing strategy.

egies described earlier: the amount of information processed, the selectivity of information acquisition, and the relative degree of alternative-based and attribute-based processing. Therefore, we must translate the strategy-based results of the simulation into statements about these aspects. In particular, if we expect more use of a strategy that processes all relevant information and makes trade-offs (WADD) under negative correlation, then we should observe a greater amount of information processed, less selectivity, and more alternative-based processing under negative correlation, especially for low dispersion. Put another way, we expect a relative decrease in the use of heuristic strategies under negative correlation.

We should note that although use of the WADD strategy becomes more attractive under negative correlation, individuals may find the WADD strategy difficult to implement. In the General Discussion section, we discuss issues of strategy implementation and the degree to which individuals may attempt various approximate simplifications of the WADD strategy. Such approximations lead to the same predictions about aspects of processing as those outlined earlier but are simpler to implement.

Although these predictions inferred from the simulation results are perhaps interesting in their own right, there is little direct behavioral evidence for them, as noted ear-

lier. Therefore, we designed experiments to investigate whether people adapt to correlation as the simulations suggested.

### Overview of Empirical Investigations

The two experiments we conducted examined the degree to which human decisionmakers adapt their processing to the degree of interattribute correlation and other factors. The basic hypotheses implied by the simulation results were examined to determine whether individuals would vary their behavior in directions consistent with our accuracy-effort framework's predictions.

One common feature of these experiments provided a strong test of adaptivity. All factors varied within subjects, and the order of the stimuli was randomized for each subject. Thus, subjects who wished to adapt to the task had to infer information about the correlational structure of each choice problem by examining the values of the attributes for that particular problem because different levels of correlation appeared across choice problems. Subjects were then expected to switch strategies from one trial to the next if they were attempting to be adaptive.

## Experiment 1

As noted earlier in the description of the simulation, examining problems varying in both interattribute correlation and dispersion provides an interesting combination of context variables. Hence, like the simulation, our first experiment examined choice problems that varied in levels of interattribute correlation (positive and maximum average negative) and levels of dispersion in probabilities (low and high). On the basis of the simulation results reported earlier, our hypotheses are as follows:

H1: We hypothesized less use of heuristic strategies in negatively correlated environments. Therefore, in negatively correlated environments, decisionmakers were expected to process more information, be less selective in processing, and be more alternative-based processors than in positively correlated environments.

H2: The use of heuristic strategies should be lowest in environments characterized by both low dispersion in probabilities and negative interattribute correlation structures. Thus, we expected the processing of information to be more extensive, less selective, and more alternative based for the choice environments that combined both negative correlations and low dispersion in probabilities.

Although we expected decisionmakers to attempt to adapt to negative correlation (particularly with low dispersion) by processing more information, being less selective, and using more alternative-based processing, this does not necessarily mean that people will be more accurate. On the contrary, although they may intend to attain high accuracy levels, choosing the best option would be more difficult in the negative intercorrelation conditions. Because the differences among the EVs were smaller for the negative correlation condition, it may be harder to distinguish among options.

In addition, strategies that use more information and that make trade-offs are more cognitively demanding: Mentally calculating approximate EVs can be difficult (we discuss ways individuals may try to simplify such calculations in the General Discussion section). Paquette and Kida (1988), for example, reported that the difference between the potential accuracy of a strategy and the accuracy actually realized by decisionmakers was much greater for the WADD strategy than for the less complex EBA heuristic (which is selective and avoids trade-offs). Hence, we expected decisionmakers to be generally less accurate in the negative correlation conditions, particularly under low dispersion (because more attributes must be considered to try to make an accurate choice, and the mental calculations are therefore harder). However, in keeping with the general notion of adaptivity, we also expected that decisionmakers who exhibited a greater degree of adaptivity to differences in correlation would have relatively better performance. We therefore hypothesized the following:

H3a: Performance should be lower in negatively correlated than in positively correlated environments, particularly under low dispersion.

H3b: Performance should be positively related to the degree of adaptivity in processing across correlation environments, particularly under low dispersion.

Finally, for completeness, we expected dispersion to have effects that replicated those found in our previous work (e.g.,

Creyer et al., 1990; Payne et al., 1988). More specifically, we expected the low-dispersion condition to be characterized by the processing of more information, by less selective processing, and by more alternative-based processing. Because performance was equivalent across dispersion levels in some of our prior work (Payne et al., 1988) and was poorer under low dispersion in other studies (e.g., Creyer et al., 1990), we did not have a specific hypothesis for performance.

## Method

*Subjects.* Subjects were 34 undergraduates at Duke University. Participation in the study earned credit toward fulfillment of a course requirement. In addition, 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 had possible payoffs ranging from \$0.01 to \$9.99. Every option in a particular set was defined in terms of the same four outcome probabilities. Probabilities ranged from .01 to .86 and were constrained to total one.

We used the same IMSL subroutine used in the simulation, RNMVN, to construct eight sets of options drawn from a population with a positive interattribute correlation of .6. Eight sets of options were also sampled from a population with the maximum average negative interattribute correlation for four attributes of  $-.33$ , as noted earlier.<sup>6</sup> Eight sets of probabilities low in dispersion were then generated and assigned to the eight sets of positive correlation and eight sets of negative correlation options; eight sets of probabilities high in dispersion were then generated and assigned to the eight sets of positive correlation and eight sets of negative correlation options. Note that the same probabilities were used for two sets of options: one positive correlation and one negative correlation. Thus, there were 32 sets of options in total: 8 positive correlation and low dispersion, 8 negative correlation and low dispersion, 8 positive correlation and high dispersion, and 8 negative correlation and high dispersion. The ordering of the gambles in the display was permuted so that the outcome values for the low- and high-dispersion sets did not look identical.<sup>7</sup>

To illustrate these stimuli, a low-dispersion, positive correlation set and a low-dispersion, negative correlation set are depicted in Figure 1. Overall, the sets of options were equivalent across conditions in terms of their average EVs, although the range of EVs for the options in a set was smaller for the negative correlation condition.

In summary, there were 32 decision problems of interest (2 correlation conditions  $\times$  2 dispersion conditions  $\times$  8 replications).

<sup>6</sup> For the positive sets, the average correlation among the attribute pairs was .57. The maximum pairwise attribute correlation in a set averaged .84, and the minimum pairwise correlation averaged .24. For the negative sets, the average correlation among the attribute pairs was  $-.31$ . The most negative pairwise correlation in a set averaged  $-.69$ , and the least negative pairwise correlation averaged  $-.05$ .

<sup>7</sup> Twenty of the subjects also received 16 sets of options with zero interattribute correlation (8 high dispersion and 8 low). The responses to the positive and negative correlation trials of these subjects and of those who received only the positive and negative trials were essentially identical. The results for the zero correlation trials for the 20 subjects were generally intermediate between those for the positive and negative trials. We do not consider these zero correlation trials further.



**NEGATIVE CORRELATION**

**E.V.'S**

	Outcome 1	Outcome 2	Outcome 3	Outcome 4
Probs.	.18	.25	.28	.29
Gamble A	\$3.97	\$5.36	\$6.75	\$3.54
Gamble B	\$2.49	\$3.24	\$6.99	\$7.11
Gamble C	\$8.84	\$2.37	\$4.38	\$4.61
Gamble D	\$6.62	\$1.88	\$8.66	\$3.45

Choose One  Gamble A  Gamble B  Gamble C  Gamble D

Gamble D was chosen. Enter this box and click once to continue

E.V. mean: \$5.02  
E.V. range: \$0.53

**POSITIVE CORRELATION**

**E.V.'S**

	Outcome 1	Outcome 2	Outcome 3	Outcome 4
Probs.	.18	.25	.28	.29
Gamble A	\$4.83	\$5.12	\$6.53	\$2.47
Gamble B	\$3.98	\$1.74	\$3.72	\$2.81
Gamble C	\$4.34	\$7.68	\$3.91	\$8.83
Gamble D	\$9.47	\$6.23	\$9.58	\$9.92

Choose One  Gamble A  Gamble B  Gamble C  Gamble D

Gamble D was chosen. Enter this box and click once to continue

E.V. mean: \$5.72  
E.V. range: \$5.81

Figure 1. Examples of low-dispersion gamble sets with negative and positive correlation. (Subjects saw only gamble sets, not expected values [EVs]. Boxes were closed during the experiment. Probs = probabilities.)

Problems were given to each subject in random order. Subjects took a short break after the first half of the problems. Subjects were instructed to take as much time as they wished to acquire information about probabilities and payoffs and make a decision. Subjects took an average of roughly 40 s per trial. The total experimental session took roughly 1 hr.

*The Mouselab methodology.* Information acquisitions, response times, and choices were monitored using a software system called *Mouselab* (Johnson, Payne, Schkade, & Bettman, 1991). 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 contains information about the probabilities of the four outcomes. The next four rows of boxes contain information about the payoffs associated with the different outcomes for each alternative, respectively. At the bottom of the screen are four boxes that are used to indicate which alternative was the most preferred.

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 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. Note that allowing only one box to be open at a time should make correlation even more difficult to detect.

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 1 s.

The Mouselab methodology closely resembles 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 Fitt's law indicated that one could move between boxes in less than 100 ms (Card, Moran, & Newell, 1983). This suggests that the time to acquire information using the Mouselab system is limited mainly by the time it takes to think about 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 (Payne et al., 1993).

*Dependent measures.* Information acquisition and decision behavior can be characterized in many ways (Klayman, 1983). To examine Hypotheses H1 and H2, we considered five measures of aspects of decision processing. One important aspect was the total amount of processing. One measure of amount was the total number of times information boxes were opened for a particular decision, denoted acquisitions (ACQ). A second measure was the time taken for a trial (TIME). Because of skewness in the data, log transforms of time and acquisitions were used in the analyses (Winer, Brown, & Michels, 1991, p. 355). When mean values are reported for time and acquisitions, they are exponential transforms of the mean logarithms for each condition.

The next two measures reflected the relative attention devoted to specific types of information and hence were relevant to characterizing selectivity in processing. These measures were the variances in the proportions of time spent on each alternative (VAR-ALTER) and on each attribute (VAR-ATT). 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; by contrast, noncompensatory strategies (e.g., EBA, LEX, and SAT) imply more variance in processing.

A final measure of processing characterized 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 involved the same alternative but a 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. The WADD strategy would be characterized by a positive value of PATTERN, for example, whereas such attribute-based heuristics as LEX and EBA would be characterized by negative values.

In addition to these five measures of processing, a measure of relative accuracy, defined in terms of EV maximization and random choice, was developed and denoted GAIN. Finally, a seventh variable was examined that was given a value of 1 if the individual selected the gamble with the highest EV and 0 if not. This variable was called EVMAX. These variables were used to examine Hypotheses H3a and H3b.

*Procedure.* Each subject was run individually and was told that the purpose of the experiment was to understand how people make decisions 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 that 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 before beginning on the sets of options.

## Results

The means for the measures described earlier are presented in Table 3. A multivariate analysis (MANOVA) is presented first, followed by a discussion of the results for the effects of correlation, the effects of dispersion, and the interaction between dispersion and correlation.

*MANOVA.* Because the process measures potentially are intercorrelated, the data were initially analyzed using a MANOVA with two within-subjects variables (correlation and dispersion). The analysis included the five processing measures described earlier and the relative accuracy measure. The means for these measures are provided in Table 3. There were significant main effects of correlation, [ $F(6, 1020) = 40.5, p < .0001$ ], and dispersion, [ $F(6, 1020) = 71.8, p < .0001$ ]. In addition, there was a significant Correlation  $\times$  Dispersion interaction, [ $F(6, 1020) = 14.1, p < .0001$ ].

*Effects of correlation.* Recall that we hypothesized in H1 that subjects would devote more effort, be less selective, and be more alternative-based in their processing in negatively correlated environments. In H3a, we proposed that performance would be poorer for negative correlation problems. As

Table 3  
*Process and Performance Measures as a Function of Dispersion and Correlation:  
 Experiment 1*

Dependent measure	Negative correlation		Positive correlation	
	Low dispersion	High dispersion	Low dispersion	High dispersion
ACQ	46.8	32.2	32.2	28.7
TIME	48.2	33.5	33.3	30.1
VAR-ATT	.015	.044	.017	.040
VAR-ALTER	.014	.024	.022	.028
PATTERN	.29	-.08	.22	-.10
GAIN	.33	.81	.88	.90
EVMAX	.43	.76	.85	.85

*Note.* ACQ = number of acquisitions; TIME = time taken; VAR-ATT = variance in the proportion of time spent on each attribute; VAR-ALTER = variance in the proportion of time spent on each alternative; PATTERN = index reflecting relative amount of attribute-based (-) and alternative-based (+) processing; GAIN = relative accuracy of choices; EVMAX = proportion of highest expected value choices.

expected, subjects devoted more processing effort to negative correlation choices as compared with positive correlation choices. Negative correlation choices were characterized by more ACQ ( $M_s = 38.8$  vs.  $30.4$ , respectively),  $F(1, 1025) = 88.3, p < .0001, MS_e = 0.18$ , and more TIME ( $M_s = 40.2$  vs.  $31.7$ , respectively),  $F(1, 1025) = 85.9, p < .0001, MS_e = 0.18$ .

In addition to devoting more effort, subjects exhibited the processing differences we hypothesized across negative and positive correlation environments. Negative correlation choices were characterized by lower selectivity across alternatives (VAR-ALTER;  $M_s = .019$  vs.  $.025$ , respectively),  $F(1, 1025) = 27.5, p < .0001, MS_e = .0003$ , although there was no significant difference in selectivity across attributes (VAR-ATT;  $M_s = .029$  vs.  $.029$ , respectively),  $F(1, 1025) = .17, ns, MS_e = .0009$ . Individuals were also more likely to process by alternative in negative correlation environments (PATTERN;  $M_s = .11$  vs.  $.06$ , respectively),  $F(1, 1025) = 4.9, p < .05, MS_e = .13$ . Thus, individuals in the negative correlation environment changed their processing to be less selective over alternatives and to be more alternative based.

Despite these changes, individuals performed less well in the more difficult negative correlation environment both in terms of relative accuracy (GAIN;  $M_s = .57$  vs.  $.89$ , respectively),  $F(1, 1025) = 131.2, p < .0001, MS_e = .21$ , and proportion correct (EVMAX;  $M_s = .60$  vs.  $.85$ , respectively),  $\chi^2(1, N = 1088) = 12.2, p < .001$ .<sup>8</sup>

*Effects of dispersion.* The main effects of dispersion were as expected and replicated our earlier findings. Low dispersion, compared with high dispersion, resulted in more ACQ ( $M_s = 38.8$  vs.  $30.4$ , respectively),  $F(1, 1025) = 88.6, p < .0001, MS_e = 0.18$ , more TIME ( $M_s = 40.7$  vs.  $31.8$ , respectively),  $F(1, 1025) = 82.1, p < .0001, MS_e = .18$ , lower variance in processing across attributes (VAR-ATT;  $M_s = .016$  vs.  $.042$ , respectively),  $F(1, 1025) = 206.6, p < .0001, MS_e = .0009$ , lower variance in processing across alternatives (VAR-ALTER;  $M_s = .018$  vs.  $.026$ , respectively),  $F(1, 1025) = 61.0, p < .0001, MS_e = .0003$ , and more alternative-based processing (PATTERN;  $M_s = .25$  vs.  $-.09$ , respectively),  $F(1, 1025) = 251.2, p < .0001, MS_e = .13$ . The

performance findings show that low dispersion resulted in lower relative accuracy (GAIN;  $M_s = .60$  vs.  $.85$ , respectively),  $F(1, 1025) = 79.7, p < .0001, MS_e = .21$ , and fewer correct selections (EVMAX;  $M_s = .64$  vs.  $.81$ , respectively),  $\chi^2(1, N = 1088) = 15.4, p < .0001$ . Thus, low dispersion led to more processing, less selective processing, more alternative-based processing, and lower performance. These processing results are consistent with the adaptations to dispersion suggested by the simulation.

*Effects of Correlation  $\times$  Dispersion.* These main effects were not the only effects of interest. We argued in Hypotheses H2 and H3a that the low-dispersion, negative correlation condition would be particularly difficult. Several significant Correlation  $\times$  Dispersion interactions showed this to be true. There were significant interactions for number of ACQ,  $F(1, 1025) = 25.4, p < .0001, MS_e = 0.18$ , TIME,  $F(1, 1025) = 27.0, p < .0001, MS_e = 0.18$ , relative accuracy,  $F(1, 1025) = 65.8, p < .0001, MS_e = .21$ , and correctness of choice,  $\chi^2(1, N = 1088) = 16.3, p < .0001$ . There were marginally significant interactions for selectivity across attributes,  $F(1, 1025) = 2.9, p = .09, MS_e = .0009$ , and selectivity across alternatives,  $F(1, 1025) = 2.7, p = .10, MS_e = .0003$ . As shown in Table 3, all of these interactions have the same form: The low-dispersion, negative correlation cell stands out. This cell received much more effort, displayed somewhat less selectivity, and was characterized by much lower performance. There was no significant interaction for processing pattern,  $F(1, 1025) = 1.0, ns, MS_e = .13$ .

*Adaptivity to correlation and performance.* The analyses just reported reflected group performance levels across various sets of gambles and subjects. We also examined the degree to which an individual subject's degree of adaptivity to correlation would be related to performance. The results of the simulation showed that accuracy differences attributable to correlation were highly pronounced under low dispersion. In addition, the significant Correlation  $\times$  Dispersion

<sup>8</sup> For analyses of correct selections, we used a logistic regression analysis.

interaction reported earlier showed that the negative correlation, low-dispersion environment differed from the other three conditions with respect to accuracy. Therefore, we focused our examination of adaptivity on the problems involving negative correlation, low dispersion and positive correlation, low dispersion. Hypothesis H3b stated that the greater the adaptation to correlation differences, the higher the overall performance levels. We tested this with a correlational analysis.

First, recall that there were eight sets of probabilities low in dispersion and that the same probability values were used for pairs of two sets of options, one set with positive correlation and one set with negative correlation. Figure 1 illustrates such a pair. Hence, there were eight pairs of gamble sets in which the two sets in the pair had the same probabilities, although correlation levels and the range of EVs differed across the two gamble sets. For each pair, we computed the difference between the positive correlation gamble set and the negative correlation gamble set for the processing and effort variables (positive-negative). These differences represent indicators of the extent to which each subject was adapting to the level of correlation, holding dispersion constant (low). For each pair, we also calculated the average GAIN score. We then tested the extent to which the degree of adaptivity was related to performance by pooling the responses for the eight pairs per subject over all subjects and correlating the difference scores with the average GAIN. If our hypotheses about adaptivity are correct, we would expect negative correlations between the difference scores and average GAIN for ACQ, TIME, and degree of alternative-based processing and positive correlations between the difference scores and average GAIN for the selectivity measures. These expectations were derived from our hypotheses that more adaptive subjects would devote more effort, be less selective, and be more alternative based for negative correlation sets and would also exhibit better performance overall.

The correlational analysis showed that the degree of adaptivity (the difference scores) and average GAIN were significantly related in the hypothesized direction for ACQ ( $r$

$= -.14, p < .02$ ), TIME ( $r = -.14, p < .02$ ), and degree of alternative-based processing ( $r = -.13, p < .03$ ). The relations were not significant for selectivity over alternatives ( $r = .08$ ) or selectivity over attributes ( $r = -.02$ ). We also constructed a composite adaptivity score; the five processing-variable difference scores were averaged (after standardizing the individual variable scores and reversing the signs for the two selectivity measures). As we noted earlier, we expected this composite score to be negatively correlated with average GAIN, and it was ( $r = -.15, p < .01$ ). Thus, there is support for Hypothesis H3b: Subjects who adapted more to different correlation levels were better performers.

*Analysis with range of expected values as a covariate.* As noted earlier, the range of EVs for the options in a set was smaller for the negative correlation sets because of the way in which the sets for the two correlation conditions were constructed. Hence, it is possible that our results reflect this confound between EV range and correlation rather than any other aspect of correlation. We could examine this possibility by performing an analysis in which the range of EVs for each set was included in the analysis as a covariate, thus removing the effects of range. We ran this analysis, and the least squares means are reported in Table 4. The proportion correct means listed are the original means because the logistic regression used did not calculate the equivalent of least squares means. The effects of correlation can now be examined uncontaminated by the effects of range.

A MANOVA showed significant main effects due to correlation,  $F(6, 1019) = 5.2, p < .0001$ , and dispersion,  $F(6, 1019) = 32.5, p < .0001$ . In addition, there was a significant Correlation  $\times$  Dispersion interaction,  $F(6, 1019) = 3.0, p < .01$ . Note that although the effects were significant, they are weaker than in the previous analysis.

The main effects of correlation were similar to those just reported. Negative, as opposed to positive, correlation choices were characterized by more ACQ ( $M_s = 36.2$  vs.  $32.7$ , respectively),  $F(1, 1024) = 5.5, p < .02, MS_e = 0.18$ , more TIME ( $M_s = 38.1$  vs.  $33.7$ , respectively),  $F(1, 1024) = 6.1, p < .02, MS_e = 0.18$ , more alternative-based pro-

Table 4  
*Process and Performance Measures as a Function of Dispersion and Correlation With Range of Expected Values as a Covariate: Experiment 1*

Dependent measure	Negative correlation		Positive correlation	
	Low dispersion	High dispersion	Low dispersion	High dispersion
ACQ	39.9	32.9	35.0	30.6
TIME	42.4	34.1	35.7	31.8
VAR-ATT	.014	.044	.018	.040
VAR-ALTER	.017	.024	.020	.027
PATTERN	.38	-.08	.17	-.13
GAIN	.43	.79	.83	.86
EVMAX	.43	.76	.85	.85

*Note.* ACQ = number of acquisitions; TIME = time taken; VAR-ATT = variance in the proportion of time spent on each attribute; VAR-ALTER = variance in the proportion of time spent on each alternative; PATTERN = index reflecting relative amount of attribute-based (-) and alternative-based (+) processing; GAIN = relative accuracy of choices; EVMAX = proportion of highest expected value choices. Least squares means are reported for all measures except EVMAX, for which the raw means are presented.

cessing ( $M_s = .15$  vs.  $.02$ , respectively),  $F(1, 1024) = 3.8$ ,  $p < .05$ ,  $MS_e = .13$ , lower relative accuracy ( $M_s = .61$  vs.  $.85$ , respectively),  $F(1, 1024) = 16.9$ ,  $p < .0001$ ,  $MS_e = .21$ , and lower proportion correct ( $M_s = .60$  vs.  $.85$ , respectively),  $\chi^2(1, N = 1088) = 12.6$ ,  $p < .001$ . There were no significant differences for either selectivity across alternatives ( $M_s = .021$  vs.  $.023$ , respectively),  $F(1, 1024) = 2.1$ ,  $ns$ ,  $MS_e = .0003$ , or selectivity across attributes ( $M_s = .029$  vs.  $.029$ , respectively),  $F(1, 1024) = 1.1$ ,  $ns$ ,  $MS_e = .0009$ .

The results are also similar to our original analysis for the effects of dispersion. Low dispersion resulted in more ACQ ( $M_s = 37.4$  vs.  $31.7$ , respectively),  $F(1, 1024) = 19.7$ ,  $p < .0001$ ,  $MS_e = 0.18$ , more TIME ( $M_s = 38.9$  vs.  $32.9$ , respectively),  $F(1, 1024) = 17.9$ ,  $p < .0001$ ,  $MS_e = 0.18$ , lower selectivity across alternatives ( $M_s = .019$  vs.  $.026$ , respectively),  $F(1, 1024) = 23.9$ ,  $p < .0001$ ,  $MS_e = .0003$ , lower selectivity across attributes ( $M_s = .016$  vs.  $.042$ , respectively),  $F(1, 1024) = 171.1$ ,  $p < .0001$ ,  $MS_e = .0009$ , more alternative-based processing ( $M_s = .28$  vs.  $-.11$ , respectively),  $F(1, 1024) = 201.5$ ,  $p < .0001$ ,  $MS_e = .13$ , lower relative accuracy ( $M_s = .63$  vs.  $.83$ , respectively),  $F(1, 1024) = 12.6$ ,  $p < .001$ ,  $MS_e = .21$ , and lower proportion correct ( $M_s = .64$  vs.  $.81$ , respectively),  $\chi^2(1, N = 1088) = 16.5$ ,  $p < .0001$ .

The results differed more from those of our original analyses when we examined the Correlation  $\times$  Dispersion interaction. There were significant interactions for processing pattern,  $F(1, 1024) = 4.6$ ,  $p < .05$ ,  $MS_e = .13$ , relative accuracy,  $F(1, 1024) = 11.4$ ,  $p < .001$ ,  $MS_e = .21$ , and proportion correct,  $\chi^2(1, N = 1088) = 13.6$ ,  $p < .001$ . However, the interactions were not significant for ACQ,  $F(1, 1024) = 0.4$ ,  $ns$ ,  $MS_e = 0.18$ , TIME,  $F(1, 1024) = 1.2$ ,  $ns$ ,  $MS_e = 0.18$ , selectivity across attributes,  $F(1, 1024) = 1.2$ ,  $ns$ ,  $MS_e = .0009$ , or selectivity across alternatives,  $F(1, 1024) = 0.04$ ,  $ns$ ,  $MS_e = .0003$ . However, Table 4 shows that, as in the previous analysis, the low-dispersion, negative correlation cell stands out directionally, even when the interactions are not significant.

*An alternative hypothesis: Differences between the top two alternatives.* We have analyzed the effects of range of EVs, but there is another alternative hypothesis that must be addressed. In the negative correlation environments, there will tend to be smaller differences in EV between the top two options. Hence, subjects may need to process information more thoroughly in negative correlation conditions in order to discriminate between the two. To examine this possibility, we performed an analysis in which the difference in EVs between the top two alternatives was included as a covariate instead of using the total range of EVs as a covariate.

A MANOVA showed significant main effects for correlation,  $F(6, 1019) = 8.8$ ,  $p < .0001$ , and dispersion,  $F(6, 1019) = 53.9$ ,  $p < .0001$ . There was also a significant Correlation  $\times$  Dispersion interaction,  $F(6, 1019) = 6.5$ ,  $p < .0001$ . Note that these results are stronger than those using the range of EVs as a covariate. In addition, the effects on individual dependent variables were highly similar to those found in the original analyses with no covariate (because the least squares means for the covariance analysis were gen-

erally similar to those reported in Table 3, we do not report them). Negative correlation choices were characterized by more ACQ,  $F(1, 1024) = 28.8$ ,  $p < .0001$ ,  $MS_e = 0.18$ , more TIME,  $F(1, 1024) = 30.5$ ,  $p < .0001$ ,  $MS_e = 0.18$ , marginally more alternative-based processing,  $F(1, 1024) = 2.8$ ,  $p < .10$ ,  $MS_e = .13$ , less selectivity across alternatives,  $F(1, 1024) = 5.1$ ,  $p < .03$ ,  $MS_e = .0003$ , and lower relative accuracy,  $F(1, 1024) = 88.1$ ,  $p < .0001$ ,  $MS_e = .21$ . There were no significant differences for selectivity across attributes,  $F(1, 1024) = 0.5$ ,  $ns$ ,  $MS_e = .0009$ , or proportion correct,  $\chi^2(1, N = 1088) = 0.3$ ,  $ns$ . Hence, all results other than those for processing pattern (which dropped to marginal significance with the covariate) and proportion correct (nonsignificance with the covariate) mirror those in the original analysis.

The results with the covariate were essentially the same as the original results for dispersion. Low dispersion led to more ACQ,  $F(1, 1024) = 58.9$ ,  $p < .0001$ ,  $MS_e = 0.18$ , more TIME,  $F(1, 1024) = 54.9$ ,  $p < .0001$ ,  $MS_e = 0.18$ , lower selectivity across alternatives,  $F(1, 1024) = 43.6$ ,  $p < .0001$ ,  $MS_e = .0003$ , lower selectivity across attributes,  $F(1, 1024) = 199.0$ ,  $p < .0001$ ,  $MS_e = .0009$ , more alternative-based processing,  $F(1, 1024) = 237.5$ ,  $p < .0001$ ,  $MS_e = .13$ , lower relative accuracy,  $F(1, 1024) = 58.5$ ,  $p < .0001$ ,  $MS_e = .21$ , and lower proportion correct,  $\chi^2(1, N = 1088) = 4.1$ ,  $p < .05$ .

Finally, the results for the Correlation  $\times$  Dispersion interaction are comparable to those of our original analyses. There were significant interactions for ACQ,  $F(1, 1024) = 4.2$ ,  $p < .05$ ,  $MS_e = 0.18$ , TIME,  $F(1, 1024) = 5.4$ ,  $p < .02$ ,  $MS_e = 0.18$ , and relative accuracy,  $F(1, 1024) = 35.6$ ,  $p < .0001$ ,  $MS_e = .21$ . There was also a marginally significant interaction for proportion correct,  $\chi^2(1, N = 1088) = 3.2$ ,  $p < .08$  (significant in the original analysis). As previously, the low-dispersion, negative correlation condition stood out. There were no significant interactions for processing pattern,  $F(1, 1024) = 0.4$ ,  $ns$ ,  $MS_e = .13$ , selectivity across attributes,  $F(1, 1024) = 0.5$ ,  $ns$ ,  $MS_e = .0009$  (marginally significant in the original analysis), and selectivity across alternatives,  $F(1, 1024) = 0.1$ ,  $ns$ ,  $MS_e = .0003$  (marginally significant in the original analysis).

Although there are some differences between these results and those of our original analysis, most of the significant effects remain. Hence, these analyses using the difference in EV between the top two alternatives as a covariate do not support the alternative hypothesis described earlier.

Taken together, the results of these analyses support the hypothesized effects of correlation on the amount and pattern of processing and on performance. Negative correlation led to more processing, more alternative-based processing, and lower performance. The results are more mixed for selectivity in processing, with no support for lower selectivity under negative correlation when the range covariate was included. Finally, there is some support for the notion that processing patterns would be particularly different in the negative correlation, low-dispersion condition, although the exact form of that support depended on the analysis.

### Discussion

The results of Experiment 1 demonstrate that individuals adapt to interattribute correlation in a situation in which such adaptivity requires the correlation structure to be inferred on a trial-by-trial basis. To our knowledge, these results are the first unambiguous demonstration of sensitivity to correlation at the detailed, information-processing level. Individuals appear to use different types of processing for problems characterized by different levels of correlation.

In addition, the specific form of the adaptivity was generally in the directions predicted by the simulation work on the basis of our effort-accuracy approach. Individuals processed negative correlation choice problems in ways that involved more processing and more alternative-based processing, especially when dispersion was low. There was mixed evidence for lower selectivity. There was also some evidence that the low-dispersion, negative correlation condition stood out in terms of processing. These results support the idea that individuals attempt to confront conflict and do not support the notions that individuals either avoid conflict or do not notice the degree of correlation or conflict present.

Individuals do not respond perfectly to correlation structure, however. Despite the processing changes, performance still suffers in the negative correlation environment, especially under low dispersion. Hence, individuals may intend to attain high accuracy but may not be able to actually implement the required mental calculations. As noted earlier, we discuss implementation issues more fully in the General Discussion section.

We were somewhat surprised that subjects adapted their processing patterns as much as they did in response to the different correlational environments given the previous lack of results and prior work showing difficulties in assessing correlation (Crocker, 1981). It is possible that subjects were responding to conflict or choice difficulty rather than correlation per se; that is, it may be more apparent in the negative correlation cells that there are no "easy" choices—to get a higher value on one outcome one generally has to give up something on another outcome. We discuss what subjects were noticing in more detail in the General Discussion section.

In Experiment 2, we attempted to test subjects' abilities to adapt to an even more difficult manipulation involving correlation. In particular, we devised a correlational environment in which using a strategy that was normally highly adaptive would in fact backfire. If subjects respond to such a "misleading" environment in ways that are in fact reasonable, this would constitute extremely impressive evidence for adaptivity in decision making. In addition, we constructed the stimuli so that the range of EVs would be the same across conditions, thus removing one problem characterizing Experiment 1.

### Experiment 2

Prior research (Creyer et al., 1990; Payne et al., 1988) and the results of Experiment 1 demonstrate that when faced with choice problems characterized by high disper-

sion in probabilities (weights), people shift toward strategies characterized by less processing, greater selectivity in processing (particularly across attributes), and more attribute-based processing. Although such a strategy shift is usually adaptive, in that accuracy can be maintained with a substantial savings of effort (see Payne et al., 1988), such a shift in strategy could be nonadaptive in certain environments. In this experiment, we specifically manipulated the gamble sets so that choices based on the normally reasonable selective, attribute-based strategy would be poor choices. In so doing, we consciously set up a situation in which the implications of adapting to one context variable (high dispersion in probabilities) would be inconsistent with what would be required to adapt to another context variable related to interattribute correlation. In particular, for high-dispersion choices with a special underlying structure (described next), we examined whether individuals would adapt to situations in which selectively concentrating on high-probability outcomes would be misleading. Before describing our hypotheses, we provide some details about this underlying correlational structure.

### Misleading Cue Manipulation

We constructed 16 sets of gambles as eight matched pairs. All gambles in all 16 sets had probabilities characterized by high dispersion. We constructed the pairs by arranging the payoffs on the most important (most probable) attribute in two different ways. We developed eight gamble sets (the "misleading cue" sets) by arranging the payoffs so that the ranking of outcome values on the most important attribute was exactly the opposite of the overall rank ordering of EVs for the gambles in that set. For example, for the misleading cue sets, the gamble with the highest payoff on the most important attribute had the lowest EV. We constructed a control "twin" for each of these "misleading" sets by reordering the outcome values on the most important attribute so that this ordering matched the ordering of EVs. In addition (and unlike the stimuli in Experiment 1), we manipulated the payoffs so that the control and misleading pairs had roughly equivalent means and ranges of EVs for the gambles in the set. Examples of a misleading and control pair are shown in Figure 2.

This procedure for constructing the misleading gambles induced an interattribute correlation structure. In particular, the misleading sets were characterized by negative Pearson product-moment correlations between the outcome with the highest probability and the other three outcomes (the average negative correlations were  $-.92$ ). The other three outcomes were also all positively correlated among themselves (the average positive correlations were  $.79$ ). For the control sets, in most cases the outcome with the highest probability was positively correlated with two other outcomes (the average positive correlations were  $.73$ ), and they were all negatively correlated with a fourth outcome (this fourth outcome varied from set to set in terms of its rank order on probability; the average negative correlations were  $-.68$ ). This correlation structure is fairly complex, and it is possible that subjects

**E.V.'s**

**CONTROL GAMBLE SET**

	Outcome 1	Outcome 2	Outcome 3	Outcome 4
Probs.	.21	.55	.15	.09
Gamble A	\$2.03	\$4.70	\$2.98	\$7.68
Gamble B	\$7.50	\$5.32	\$8.32	\$7.23
Gamble C	\$8.98	\$5.79	\$9.47	\$2.90
Gamble D	\$2.97	\$4.87	\$3.03	\$8.37
Choose One	Gamble A	Gamble B	Gamble C	Gamble D
Gamble D was chosen. Enter this box and click once to continue				

E.V. mean: \$5.45  
E.V. range: \$1.36

**E.V.'s**

**MISLEADING GAMBLE SET**

	Outcome 1	Outcome 2	Outcome 3	Outcome 4
Probs.	.21	.55	.15	.09
Gamble A	\$2.03	\$5.79	\$2.98	\$1.02
Gamble B	\$7.50	\$4.87	\$8.32	\$9.23
Gamble C	\$8.98	\$4.70	\$9.47	\$9.56
Gamble D	\$2.97	\$5.32	\$3.03	\$8.37
Choose One	Gamble A	Gamble B	Gamble C	Gamble D
Gamble D was chosen. Enter this box and click once to continue				

E.V. mean: \$5.50  
E.V. range: \$1.35

Figure 2. Examples of misleading and control gamble sets. (Subjects saw only gamble sets, not expected values [EVs]. Boxes were closed during the experiment. Probs = probabilities.)

reacted to conflict or problem difficulty instead of directly to assessed correlation. We discuss this issue further in the General Discussion section.

*Hypotheses*

On the basis of our previous findings that subjects were adaptive, we hypothesized that individuals would adapt to even this difficult decision environment. What does adaptivity mean in this experimental situation? We set up an environment in which being selective and attribute based would work well for the control sets but would backfire for misleading sets. Therefore, if subjects notice the structure of the stimuli and attempt to adapt, they should do more processing, be less selective, and be more alternative based for misleading sets. Because the structure of the stimuli may require some time to assess, these differences may become apparent only for later choices.

As in Experiment 1, although subjects might have intended to attain high accuracy by changing their processing, their performance might still have suffered. Even though the ranges in EVs were equated for the control and misleading sets, it was more difficult to accurately perform the mental calculations (strategies) needed to perform well for the misleading sets than those required for the control sets. That is, for the control sets, simply focusing on one attribute would suffice, whereas for the misleading sets, an alternative strategy that required trade-offs across two or more attributes would be necessary for good performance. Hence, we expected that performance would still be poorer for the misleading sets. However, we expected once again that the greater the adaptivity shown to the difference between misleading and control sets of gambles, the better the performance.

*Method*

*Subjects.* Twenty-six Duke University undergraduates served as subjects. They earned credit toward fulfillment of a course requirement for participation. In addition, subjects could win as much as \$9.99 by playing a gamble that was based on their actual choices.

*Stimuli.* The stimuli were sets of four risky options, each with four outcomes ranging in probability from .05 to .72. Every option in a particular option set had the same four outcome probabilities. The outcomes had possible payoffs ranging from \$0.01 to \$9.99. Only one within-subjects variable, cue type (misleading or control), was manipulated. The 16 decision problems were presented to each subject in a different random order. Each trial took roughly 50 s. The total experiment took roughly 30 min.

*Procedure.* Decision problems were again presented using the Mouselab system. Each subject was run individually and was told to choose the gamble he or she would most prefer to play. Subjects were also told that at the end of the experiment, 1 of the 16 gamble sets would be selected at random and that the option they had selected would be played by randomly generating an outcome according to the probabilities for that set. They were allowed to keep any money they had won. Depending on their choices and the random process, subjects could win between \$0.01 and \$9.99. After receiving instructions on the use of Mouselab, subjects made their 16 choices.

*Results*

The means for the dependent measures used throughout the article are provided in Table 5. Note that the means are given not only for the misleading cues sets versus the control sets but are also listed for the first and second half of the set of stimuli (i.e., the first 8 choices vs. the second 8). Examining the data in this fashion provided insights into the time required for subjects to adapt, if in fact they adapted at all.

*MANOVA.* The data were first analyzed using a MANOVA with two within-subjects variables of interest: cue type and half. The analysis included the five processing measures noted earlier and the relative accuracy measure. There were significant main effects of cue type,  $F(6, 365) = 3.0, p < .007$ , and half,  $F(6, 365) = 10.0, p < .0001$ . There was also a significant Cue Type  $\times$  Half interaction,  $F(6, 365) = 2.3, p < .04$ .

*Effects of cue type.* There were no main effects of misleading cues compared with control on ACQ ( $M_s = 37.7$  vs. 36.0, respectively),  $F(1, 370) = 2.12, ns, MS_e = 0.14$ , variance in processing across attributes ( $M_s = .021$  vs. .022, respectively),  $F(1, 370) = 0.07, ns, MS_e = .0006$ , or proportion of highest EV choices ( $M_s = .58$  vs. .60, respectively),  $\chi^2(1, N = 416) = 0.32, ns$ . There was a marginal main effect of misleading cues compared with control for TIME ( $M_s = 44.3$  vs. 42.0, respectively),  $F(1, 370) = 2.79, p < .10, MS_e = 0.12$ . There were also main effects for misleading cues relative to control sets on variance in processing across alternatives ( $M_s = .016$  vs. .021, respectively),  $F(1, 370) = 5.8, p < .02, MS_e = .0004$ , and degree of alternative-based processing ( $M_s = .18$  vs. .12, respectively),  $F(1, 370) = 4.33, p < .04, MS_e = .11$ . As expected, if subjects were attempting to adapt, the misleading cue sets were characterized by less selectivity and more alternative-based processing. There was also a marginal effect for relative accu-

Table 5  
*Process and Performance Measures as a Function of Cue Type and Half: Experiment 2*

Dependent measure	Misleading cue		Control	
	First half	Second half	First half	Second half
ACQ	37.7	37.7	42.6	30.1
TIME	47.9	41.2	49.4	35.3
VAR-ATT	.027	.017	.017	.029
VAR-ALTER	.018	.014	.016	.027
PATTERN	.15	.22	.13	.11
GAIN	.53	.60	.62	.75
EVMAX	.54	.61	.59	.61

*Note.* ACQ = number of acquisitions; TIME = time taken; VAR-ATT = variance in the proportion of time spent on each attribute; VAR-ALTER = variance in the proportion of time spent on each alternative; PATTERN = index reflecting relative amount of attribute-based (-) and alternative-based (+) processing; GAIN = relative accuracy of choices; EVMAX = proportion of highest expected value choices.



racy ( $M_s = .57$  vs.  $.68$ , respectively),  $F(1, 370) = 3.2$ ,  $p < .08$ ,  $MS_e = .36$ , again in the direction we expected.<sup>9</sup>

Although there were no main effects of cue type for some of these variables, there were several Cue Type  $\times$  Half interactions. The Cue Type  $\times$  Half interactions were significant for acquisitions,  $F(1, 370) = 12.1$ ,  $p < .001$ ,  $MS_e = 0.14$ , TIME,  $F(1, 370) = 10.8$ ,  $p < .001$ ,  $MS_e = 0.12$ , variance in processing across attributes,  $F(1, 370) = 6.3$ ,  $p < .02$ ,  $MS_e = .0007$ , and variance in processing across alternatives,  $F(1, 370) = 4.3$ ,  $p < .04$ ,  $MS_e = .0004$ . The interaction for degree of alternative-based processing had the expected form, although it was not significant,  $F(1, 370) = 1.20$ . Finally, the interactions for relative accuracy and proportion of highest EV choices were not significant,  $F(1, 370) = 0.32$ ,  $\chi^2(1, N = 416) = 0.24$ , respectively.

The form of these interactions can be seen from the data in Table 5. For both ACQ and TIME, subjects devoted roughly equal amounts of effort to misleading and control trials in the first 8 trials; however, subjects maintained their effort for misleading cues more than for control cues in the second 8 trials. The variance in processing measures showed that subjects became less selective for misleading cue trials in the second 8 trials, whereas they became more selective for control trials. These effects are in the directions we hypothesized if subjects were adapting processing strategies to the misleading cue manipulation.

*Adaptivity to cue type and performance.* The degree to which adaptivity to cue type was related to performance was examined at the level of the individual subject. Recall that the stimuli were eight paired choice sets, with each pair consisting of a control set and a paired misleading set (see Figure 2 for an example of such a pair of choice sets). Unlike in Experiment 1, the paired sets of gambles in Experiment 2 were equivalent in both means and ranges of EVs. Thus, they provided an opportunity to examine the relation between degree of adaptivity and performance with range of EVs held constant.

Difference scores between control and misleading sets were calculated for the processing and effort variables for each of the eight pairs (control-misleading). These difference scores, measuring degree of adaptivity to cue type, were then correlated with the average GAIN scores for the paired choice sets. We expected that the greater the subject's adaptivity in processing the control and misleading sets, the better the performance. Specifically, we hypothesized that the more effort (ACQ and TIME) in processing, the less selectivity in processing and that the more alternative-based processing for the misleading set relative to the control set, the higher the average GAIN. These expectations were supported for ACQ ( $r = -.17$ ,  $p < .02$ ), TIME ( $r = -.16$ ,  $p < .02$ ), selectivity over attributes ( $r = .17$ ,  $p < .02$ ), and selectivity over alternatives ( $r = .14$ ,  $p < .05$ ). The results for degree of alternative-based processing ( $r = -.11$ ,  $p < .11$ ) were in the expected direction but not significant. Once again, we constructed a compositive adaptivity score by averaging the five processing-variable difference scores (after standardizing the individual variable scores and reversing the signs for the two selectivity measures). On the basis of this reasoning, this compositive score should be negatively correlated with av-

erage GAIN, and it was ( $r = -.23$ ,  $p < .001$ ). Thus, there is again evidence that greater adaptivity by individuals leads to better performance, even though the performance over all subjects was not as good when they were faced with misleading choice problems.

### Discussion

In general, subjects adapted to the misleading cues trials, either immediately or over time, by devoting more effort, being less selective, and being more alternative based. Therefore, even in a correlational environment in which we attempted to make it difficult for subjects to respond appropriately, they changed their processing in the "correct" direction. Subjects were able to handle a situation specifically designed to put the implications of two context variables, dispersion and stimulus correlation structure, into conflict. This degree of adaptivity is highly impressive.

Over time, subjects' relative accuracy scores and proportion of highest EV choices increased, within both the misleading cues condition and the control condition (for means, see Table 5). However, subjects' adaptivity was not perfect when one considers measures of accuracy. In spite of the fact that the misleading and control sets of gambles had equivalent means and ranges of EVs, the performance for the misleading choice problems was still marginally poorer, as expected.

### General Discussion

The results of both Experiments 1 and 2 support the notions that decisionmakers adapt to correlation by confronting conflict rather than avoiding it and that an effort-accuracy perspective can predict the directions in which individuals shift their processing. Individuals also seemed to be highly sensitive to different correlational structures in our studies.

### What Did Individuals Notice?

Throughout this article, we have argued that individuals responded to the various correlation structures we presented to them. However, we have no direct evidence that individuals responded directly to assessments of correlation per se. In fact, it is somewhat unlikely that this would be the case. First, previous research has shown that individuals often have difficulties in actually assessing correlation (Alloy & Tabachnik, 1984; Crocker, 1981). Second, our Mouselab methodology did not allow individuals in our studies to simultaneously examine several pieces of information, which

<sup>9</sup> Although there were main effects of half, they corresponded to expected decreases in time and effort with increased experience with the task and were therefore of less conceptual interest than the effects of cue type or the Cue Type  $\times$  Half interactions. There were significant effects of first half compared with second half on ACQ ( $M_s = 40.1$  vs.  $33.8$ , respectively),  $F(1, 370) = 26.7$ ,  $p < .001$ ,  $MS_e = .14$ , and TIME ( $M_s = 48.6$  vs.  $38.2$ , respectively),  $F(1, 370) = 51.1$ ,  $p < .001$ ,  $MS_e = .12$ .

would hinder correlation assessments. Third, the decision problems were not blocked by level of correlation but were randomly ordered. Finally, our subjects seemed to adapt their processing well to the various conditions. Their processes would not demonstrate such adaptivity if they had to first examine much of the information in order to assess covariation. So what were individuals noticing and reacting to?

One possibility is conflict or the degree of compatibility between the implications of various attributes for choice. In the negative correlation conditions of Experiment 1, it is easy to notice quickly that there was no "easy" choice; one generally had to give up something on one outcome to obtain more on another outcome. Put another way, it is fairly easy to see quickly that the relative orderings of options were not the same across outcomes. On the other hand, these relative orderings were much more consistent for the positive correlation sets. In Experiment 2, given that the highest probability outcome was a natural initial focus, subjects could also assess fairly quickly whether other outcomes tended to agree or disagree with the highest probability outcome. For the control sets, in general, the implications of two of the other attributes agreed with the high-probability outcome; for the misleading sets, all of the other three attributes disagreed with the highest probability outcome.

We can assess the degree to which our correlation measures were associated with such ideas of conflict and compatibility. In particular, we can calculate an index to measure the degree of ordinal agreement of pairs of outcomes that is a variant of the  $V$  statistic proposed by Nelson (1984; see also Gonzalez-Vallejo & Wallsten, 1992). For any pair of outcomes, we can count the proportion of pairs of gambles ranked identically for the two outcomes. The higher the proportion, the less the conflict and the greater the compatibility in the ordering implications of those outcomes. For example, for the negative and positive correlation gamble sets shown in Figure 1, that proportion is 2 out of 6 and 4 out of 6 for the first two outcomes, respectively. Because the overall implications of the degree of agreement will presumably depend on the probabilities of the two outcomes (e.g., it may not matter whether there are disagreements in ordering for two low-probability outcomes), we can weight the proportion of agreement by the product of these probabilities, suitably normalized. If we let  $x_{ij}$  be the proportion of pairs ranked identically for outcomes  $i$  and  $j$  and denote by  $p_i$  and  $p_j$  the probabilities of outcomes  $i$  and  $j$ , then our proposed index to measure the overall degree of agreement is

$$\frac{\sum_{i > j} p_i p_j x_{ij}}{\sum_{i > j} p_i p_j}$$

The denominator simply normalizes the index so that it is more comparable across sets of gambles with different probabilities on the outcomes. Larger values of this index represent lower conflict or higher compatibility (the index would be one if all pairs of outcomes were in agreement).

For Experiment 1, the average index was .37 for the negative sets and .69 for the positive sets; for Experiment 2, the index was .22 for the misleading sets and .59 for control. Thus, our correlation manipulations also manipulated conflict and compatibility as defined by ordinal agreement or

disagreement of pairs of outcomes. Although it is perhaps more plausible to contend that subjects react to this conflict and compatibility rather than directly to correlation, we must caution that we have no direct evidence to support this contention. Future research should attempt to unravel more completely what controls individuals' behaviors in choice situations with correlated attributes.

### Strategy Implementation

Although subjects in this study adapted their *processing* well in response to correlation, performance did not always remain at high levels. Subjects might have changed their processing in ways intended to attain high accuracy; however, this high accuracy might not have been actually realized. In several of our choice environments, *implementation* of a strategy might have been highly difficult (i.e., the mental calculations required might have been hard or extensive). Hence, decisionmakers showed what might be termed *intended adaptivity*: They intended to achieve good results and switched processing in ways that seemed capable of achieving these results, but they might not have actually been able to get them. Instead, the most that shifts in processing may obtain is *relatively better* performance, not perfect adaptation.

One area that has not yet been considered within our effort-accuracy approach is the precision with which individuals can execute strategies. It may ultimately lead to better performance to use a strategy that is theoretically less accurate than a second strategy if the first strategy can be implemented more precisely than the second (see Hammond, Hamm, Grassia, & Pearson, 1987, and Paquette & Kida, 1988, for related ideas). However, individuals may tend to be overconfident concerning their abilities to execute decision strategies. Such overconfidence in one's own abilities to complete cognitive tasks is relatively common and has been referred to as "cognitive conceit" (Dawes, 1976). Thus, decisionmakers may often attempt to undertake relatively difficult strategies that would have an unfavorable effort-accuracy trade-off *if* an unbiased assessment of expected executional errors was undertaken. Research investigating effects related to errors in strategy implementation would be a significant extension of current effort-accuracy approaches.

A related issue is the degree to which individuals actually attempt to calculate the full WADD model. It seems highly unlikely that individuals could multiply three-digit payoffs by two-digit probabilities, add these products for four attributes, and do this for all four alternatives within the average time per trial of approximately 30-50 s depending on the condition. Yet, the individuals in our experiments did change their processing to be more extensive, somewhat more selective, and more alternative based under negative correlation conditions, as we hypothesized. What are individuals doing under negative correlation to simplify and approximate the WADD strategy without losing too much accuracy?

It is clear from the simulation that the simplification represented by the EQW heuristic, ignoring weights, did

poorly under negative correlation. There is also evidence from our experiments that individuals did pay attention to the probabilities: Roughly 20% of the time for each trial was spent looking at probabilities, regardless of experimental condition.

We investigated an alternative route to simplification, rounding off the payoffs and probabilities and dropping one attribute from consideration. In previous work (Bettman et al., 1990), we found that individuals instructed to follow a WADD strategy in a situation with single-digit payoffs and weights took roughly 48 s per trial to complete four-alternative, three-attribute problems. Therefore, for our correlation stimuli, we examined a simplified approximation of the WADD strategy whereby three attributes (omitting the one with the lowest probability) were considered, and both payoffs and probabilities were rounded to one digit. This simplification was similar to the WADD strategy in terms of aspects of processing (i.e., it was alternative based, examined a large proportion of the information available, and was less selective than most of the other heuristics we considered in our simulations). This simplification should be feasible to execute in roughly the time actually taken per trial by our subjects in the negative correlation conditions; it is also fairly accurate. The relative accuracy (GAIN) scores for the alternatives selected by this simplification for the stimuli used in Experiment 1 were .87 for negative correlation, low dispersion; .96 for negative correlation, high dispersion; .92 for positive correlation, low dispersion; and 1.0 for positive correlation, high dispersion. For the stimuli used in Experiment 2, the relative accuracy scores would be .78 for misleading sets and .91 for control sets.

Therefore, a relatively simple approximation to a WADD strategy, characterized by similar aspects of processing, performed well on what appeared at first glance to be highly demanding choice problems. In fact, the accuracy levels of this simplification were higher than the levels attained by our subjects. This discrepancy might have been caused by computational errors made in implementing even this simplified approximation.

We do not have any direct evidence, of course, that individuals used such a simplification. For instance, individuals may use more analogical approaches rather than attempting simplified numerical calculations (Lopes, 1982). Our point is simply that a simplification involving rounding and dropping one attribute is both reasonably feasible within the time taken by our subjects and fairly accurate. Much more research is needed to understand how individuals approximate and simplify strategies in order to bring implementation efforts within plausible limits without losing too much accuracy.

Despite the potential problems caused by such implementation issues, our subjects are impressive in the degree to which they exhibited intended adaptivity. Surely, individuals will not *always* adapt processing strategies in response to environmental variables. Under what conditions might failures be found in adaptivity in processing? There are two broad classes of factors that might lead to such failures in adaptivity. In particular, being adaptive requires various sorts of knowledge and the ability to execute strat-

egies. Deficits in either knowledge or ability may lead to failures in adaptivity.

### *Failures of Adaptivity*

Several types of deficits in knowledge may cause failures of adaptivity. First, individuals may experience difficulty in assessing properties of the decision environment. In our studies, decisionmakers did respond to correlation levels; however, in cases in which there are multiple task and context factors with conflicting implications or in cases in which the format of information makes the underlying structure non-transparent (Hammond, 1990; Tversky & Kahneman, 1988), individuals may fail to correctly assess the environment. For example, we believe that the presence of salient task variables may interfere with subjects' abilities to adapt to context variables such as correlation. Task variables are generally noticeable before acquisition of information begins, whereas context variables are generally not noticeable until several pieces of information have been acquired and interrelated. Thus, adaptation to task variables may overwhelm adaptation to more subtle context variables: Even before information search begins, subjects may undertake an a priori strategy change on the basis of the more obvious task variables. Once such a strategy change is set in motion, subjects may be reluctant to shift strategies a second time in response to context variables.

Second, individuals may also fail to adapt because they do not know the appropriate strategy, perhaps because of lack of training or experience or lack of strategic knowledge about when and how to use various procedures (Gagne, 1984). Third, individuals may not be able to correctly assess the effort and accuracy provided by a decision strategy in a particular environment. For example, individuals may not be able to easily determine the accuracy of the decision strategy they are using and may overestimate the goodness of their decision process. Finally, individuals may fail to adapt because they do not know their desired trade-off between accuracy and effort a priori, but only after the fact.

Even if a decisionmaker possesses the appropriate knowledge, he or she may fail to adapt processing if he or she cannot execute the appropriate strategy. Thus, a decisionmaker may undertake a strategy that he or she knows is not optimal because he or she believes that the optimal strategy cannot be properly executed. Environmental stressors such as time pressure, distraction, or noise; heavy memory, computational demands, or both; or losing track of one's place in a complex set of goals and subgoals can result in inability to execute or implement a strategy and, hence, to a failure to adapt. Note that failures to adapt processing on the basis of a conscious assessment that the required strategy is not feasible are distinct from the failures to maintain performance that may follow from unexpected executional errors. Therefore, although our subjects adapted to a surprising degree, there are still many situations in which adaptivity may fail. In our case, using highly intelligent and cognitively oriented Duke University undergraduates might have ensured that many of the possibilities for failure would not be met. Different subject populations may not be as adaptive.

### Summary

To summarize, our results indicate that people respond to an important context variable—interattribute correlation—by shifting their processing strategies in ways that are adaptive. They face conflict rather than avoiding it and process more information, are less selective, and show more alternative-based processing in negatively correlated environments. People adapt in ways that show sensitivity to accuracy concerns in strategy selection. The results both support an effort–accuracy approach to strategy selection and add to the growing body of data showing that people often respond highly intelligently, if not optimally, to their environment.

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