The Utilization of Configural Indicators in Decision Making

Stephen E. Edgell,

University of Louisville

J. Isaiah Harbison,

University of Maryland

Eric S. Brian,

University of Louisville

and

William P. Neace

Bellarmine University

Abstract

The use of configural information is important in decision making. Configural information is where the value of one information dimension affects the validity of another information dimension. We hypothesized that a more complex environment in which one dimension had an opposite effect on the validity of each of two other dimensions so as to indicate which of them was relevant, would be more highly utilized than the simpler case of one dimension affecting the validity of another. We tested this by training subjects in a probabilistic environment. The study confirmed our hypothesis and provided a test of two models: a hypothesis generation model and a connectionist model (RASHNL). The hypothesis generation model accounted for the general findings, but RASHNL was unable to.

Ever since Meehl (1954) hypothesized that a decision maker could process information in a configural manner and that this ability was one of the reasons the decision maker might be superior to a simple, mechanically produced judgment, configural use of information has been of much importance in the field of decision making. Configural information is where the value of one information dimension affects the validity of another dimension of information. This may be only to raise or lower the validity of the information in question or may even render it irrelevant. It may go so far as to reverse the meaning of the information in question.

A good deal of work has been done in the paradigm that Goldberg called "the search for configural judges" (Goldberg, 1968). This work has had mixed success with real world experts, but has been very fruitful when pursued in a laboratory setting where naive subjects learn the environment from feedback. This paradigm, often called non-metric probability learning, has been used to explore many aspects of decision making including the utilization of configural information. (Castellan, 1977). In this paradigm, naive subjects are trained trial by trial in a probabilistic environment. (A probabilistic environment is one of the hallmark characteristics of decision making.) On each trial the subject is first presented with one value from each of the information dimensions, or cues, and must judge the value of the criterion, or event. Then feedback in the form of the correct criterion value, event, is given. A medical decision making task is often used as a cover story for subjects. The cues are the results of medical tests run on a patient, and the event is which disease the patent has.

Early on, using this paradigm, it was found that subjects could and would learn to utilize configural information (e.g., Edgell & Castellan, 1973; Edgell, 1978; Estes, 1972; Stockburger & Erickson, 1974), but that they weighted configural information less strongly than dimensional information of the same validity (Edgell, 1993) and that the weighting of configural information further declined as the complexity of the environment increased (Edgell, 1980). Much work has followed further exploring many aspects of utilizing configural information. The present paper presents a study further expanding this line of investigation.

To understand the present work, it is first necessary to have a good understanding of the environments in which configural information utilization has previously been explored. Some examples will illustrate. The simplest decision making situation involves the choice between two alternatives. For example, a physician might have to diagnose which of two types of flu a patient has. Let's call them flu 1 and flu 2. The physician might have some information to aid in this judgment. The simplest case is where the information is one of two possible values. Let's call this information a cue and the values of it 1 and 2. To keep the example as simple as possible, suppose that flu 1 and flu 2 occur with equal frequency. That is, the base rates of flu 1 and flu 2 are .5/.5. Now suppose that when the cue is value 1, it indicates that there is a .7 probability of flu 1 and thus a .3 probability of flu 2. Further suppose that when the cue is value 2, it indicates that there is a .3 probability of flu 1 and thus a .7 probability of flu 2. Obviously, this cue has validity for diagnosing which flu strain the patient has, but it does not have perfect validity. We will call this cue a .7/.3 cue.

To involve configural information, the environment must have at least two cues that can be observed separately. Call the cues cue 1 and cue 2, each with values 1 and 2. For simplicity, assume for both cues that each cue value occurs with equal frequency, and the two cue dimensions are independent of each other. Thus, there are four joint values of the two cues (cue 1 value 1 and cue 2 value 1, cue 1 value 1 and cue 2 value 2, cue 1 value 2 and cue 2 value 1, and cue 1 value 2 and cue 2 value 2). Each of these joint values occurs with equal frequency (i.e., with probability .25). Consider the environment illustrated in Figure 1. Shown there are the conditional probabilities of flu 1 given each of the four possible patterns of cue values. Also

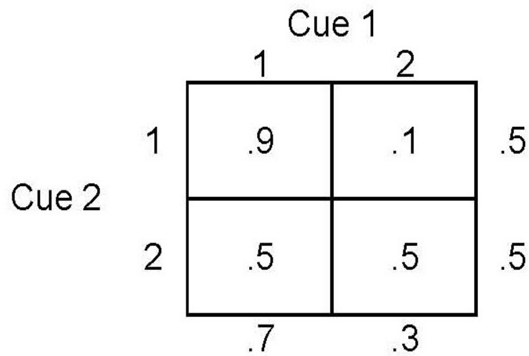

Figure 1. An example of a two, binary valued, cue dimension environment defined by the probability of flu 1 given each of the 4 possible joint values of the two cue dimensions and the marginal conditional probabilities of flu 1 given each cue value for each individual cue dimension

shown are the conditional probabilities given each individual cue. This is what the environment would appear to be if the decision maker was ignoring the other cue dimension. If the decision maker ignores cue 2, cue 1 is a .7/.3 cue. If the decision maker ignores cue 1, cue 2 is a .5/.5 cue and thus has no validity or is irrelevant. However, the value cue 2 takes on modifies the validity of cue 1. If cue 2 has value 1, then cue 1 is a .9/.1 cue, which is a higher validity than cue 1 has on the average (.7/.3). However, if cue 2 has value 2, cue 1 is a .5/.5 cue and thus has no validity. This is a typical configural situation. The value of one cue dimension modifies the validity of the other cue dimension. The reader who is familiar with analysis of variance will see that configural information is analogous to interaction. This situation has been well studied in much earlier work.

Suppose there is a third cue dimension that has an effect, similar to that just described, on the validity of the other two cue dimensions, but in opposite directions. That is, the value of cue dimension 3 determines which one of cue dimension 1 and cue dimension 2 is highly valid .9/.1 and which is irrelevant .5/.5. That is, suppose when cue 3 has value 1, cue 1 is .9/.1 and cue 2 is .5/.5, but when cue 3 has value 2, cue 1 is .5/.5 and cue 2 is .9/.1. Thus, cue 3 indicates which of the other two cues is relevant. We have chosen to call cue 3 a configural indicator because it is indicating which of two other cue dimensions is relevant and which is irrelevant. An environment with these properties is shown in Figure 2.

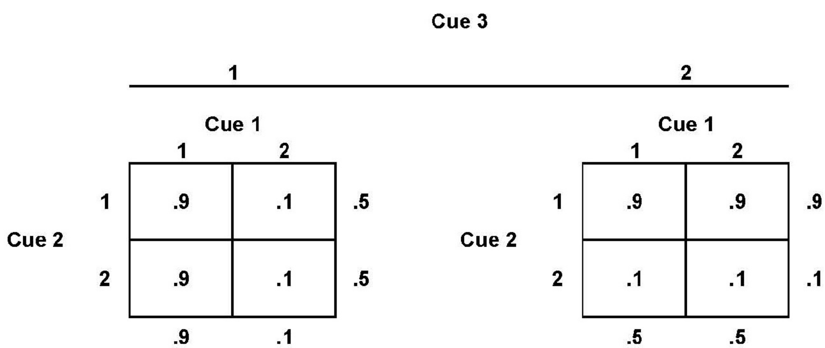

Figure 2. Environment conditional probabilities of flu 1 given each of the 8 possible joint values of the three cue dimensions for the configural indicator condition.

We propose that the situation of a configural indicator is more natural in the real world than the example given in Figure 1. No doubt there are many situations where the value of one piece of information indicates which other information dimension will be useful. The observation of one symptom may lead a physician to inquire about another symptom, but not to inquire about a different symptom or to run one particular medical test rather than some other one. It is reasonable that if configural indicators are more common, then people may well be more facile with them. Of course, the configural indicator environment with one cue having opposite effects on the validity of two other cues is a more complex environment than the more straightforward one where one cue has an effect on the validity of another cue. In the analysis of variance analogy, the configural indicator environment is one with two two-way interactions, while a configural environment, such as given in Figure 1, has only one two-way interaction. Still, we think the configural indicator is more natural. Also, as discussed later, there are currently two theories of behavior in environments such as these. One predicts a higher utilization of the configural information in the configural indicator environment than in the other configural type environment. The other model's predictions are more complex, but basically it does not predict this difference. Hence, we designed a study to test our hypothesis concerning utilization of a configural indicator.

Obviously, we want to observe subjects' performance in the configural indicator environment given in Figure 2. However, we need a suitable control condition. It is well-known that the number of dimensions will have an effect on performance (Castellan, 1973; Edgell et al., 1996). Hence, the environment in Figure 1 would not serve as a good control condition. It is necessary to have the same three cue dimensions for the control condition. However, one cue dimension varies the validity of only one other cue dimension. The remaining cue dimension is irrelevant, having no validity either as a cue dimension or as a configural modifier of the validity of another cue dimension. Having the same third cue dimension as the one that modifies the validity of another holds this factor constant with the configural indicator condition. Obviously, there are two possible such environments: one with cue dimension 3 modifying the validity of cue dimension 1 and one where cue dimension 3 modifies the validity of cue dimension 2. We ran both control conditions.

Several factors need to be considered in choosing the representation to use for the cue dimensions. It is well-known that a set of cue dimensions that creates a unitary whole greatly facilitates the use of configural information over cue dimensions that are separated (Edgell & Morrissey, 1992). It is also known that the representation of the cues can increase or decrease the utilization of them, a salience effect (Edgell et al.,1992). Fortunately, those authors found a set of equally salient stimuli; thus, we used those stimuli for the present study. Cue dimension 1 was color (red or blue), cue dimension 2 was shape (circle or triangle), and cue dimension 3 was size (smaller or larger). The exact specifications for these stimuli can be found in Edgell et al. (1992).

Method

Subjects. The subjects were 181 students who volunteered to satisfy a requirement in their introductory psychology course. Subjects were randomly assigned to the three conditions (configural indicator condition, control condition with cue 1 relevant, or control condition with cue 2 relevant).

Apparatus. The apparatus consisted of five 17" PC monitors and four similar color graphic CRTs for display of the stimuli. Responses were made using two button response boxes.

Procedure. Instructions were read to the subjects who had copies to follow along as the instructions were being read to them. The instructions explained the task. They indicated that "there are 3 sets of symptoms that might be useful in helping to distinguish between 2 flu strains." They further stated "As with real world medical tasks, it is impossible to be correct 100% of the time. Patients with the same symptoms may not have the same flu." How the symptoms would be represented and how to make responses were also explained.

On each trial a patient's set of symptoms was presented on the screen and the procedure waited for a response to be entered by pressing the button labeled “flu 1" or the button labeled “flu 2.” The response made was immediately written on the screen using a short phrase, and 0.3 sec later the correct diagnosis was written on the screen using a short phrase. The symptoms, response, and feedback remained on the screen for 1.5 sec, after which the screen was erased. After an intertrial interval of 0.5 sec, the next set of cues was presented on the screen. This procedure continued for 400 trials. Because subjects were run in groups of up to five at a time, in booths screened from view of each other, subjects who finished their 400 trials before all the others were finished were run for additional unrecorded trials until all the subjects had finished. The order of the trials was randomly permuted in blocks of 80 for each subject. Within each block of 80 trials the numbers of each type of trial (what symptoms were presented and what the correct response was) gave exactly the desired conditional probabilities. Further, each of the 8 cue patterns occurred with equal frequency.

Results and Discussion

Because the performance of the subjects after learning is of interest, the data from the last block of 80 trials were analyzed. Learning curves confirmed that the subjects had reached asymptote by the last trial block. Each subject's proportions of response "flu 1" to each of the eight stimuli patterns were calculated. These response proportions were converted to utilization weights. This gives utilization weights for each cue dimension and for the effect of each dimension of the configural information. Each weight ranges from 0, which indicates no utilization, to .5, which indicates total dependence upon that information. How the response proportions are converted to these weights has been covered in a number of sources (e.g., Edgell, 1978 & 1980; Edgell & Roe, 1995; Kruschke & Johansen, 1999), and to aid the reader is detailed in an Appendix here. Basically, it is a linear transformation using the same linear model as used in a factorial analysis of variance.

It should be noted that, for comparison, the same transformation can be applied to the environment's conditional probabilities of flu 1 given each of the eight patterns of the stimuli. This gives measures of the validity of each cue dimension and of each configural component. To aid in understanding how this measure of validity works, we note that given that each flu strain occurs equally often (a base rate of .5), a .7/.3 cue has a validity of .2 because the two cue values add or subtract .2 from the base rate of .5. (Validates always come in pairs where one is positive and one is negative but equal in absolute value. We chose to give the positive one. For utilizations, positive ones imply that the subject is using the cue or configuration in the same direction as the environment, negative ones imply that the subject is using the information in the opposite direction as the environment.) In the configural indicator condition, both cue dimension 1 and cue dimension 2 are relevant with a .2 validity. Cue dimension 3 interacts with cue dimension 1 with a validity of .2 and with cue dimension 2 also with a validity of .2. All remaining validities are 0. In each control condition, one cue dimension, either cue 1 or cue 2, has a validity of .2, the other having a validity of 0. Also, only one of the configural components has a validity of .2, the others being 0. The environmental validities are given in Table 1.

Table 1
Environment Validities

	condition		
	configural indicator	control with cue 1 relevant	control with cue 2 relevant
cue 1	.2	.2	0
cue 2	.2	0	.2
cue 3 interacting with 1	.2	.2	0
cue 3 interacting with 2	.2	0	.2

The mean utilization weights, across subjects, within conditions, from the last block of trials, are given in Table 2. The most important comparisons are the level of configural utilization between the configural indicator condition and each of the two control conditions. On the average, subjects much more highly utilized the configural information in the configural indicator condition than in both the control condition where dimension 1 was relevant ($t(119)=4.69$, $p<.001$) and in the control condition where dimension 2 was relevant ($t(120)=2.09$, $p=.038$). For completeness, we also examined the other differences between the configural indicator condition and the two control conditions as well as differences between the two control conditions. Utilization of the relevant dimension was higher in the control condition where dimension 1 was relevant than in the configural indicator condition ($t(119)=1.97$, $p=.052$), but was lower in the control condition where dimension 2 was relevant than in the configural indicator condition ($t(120)=2.09$, $p=.038$). Comparing the two control conditions, configural utilization was higher in the condition where dimension 2 was relevant ($t(117)=4.69$, $p<.001$), but utilization of the relevant dimension was higher in the condition where dimension 1 was relevant ($t(117)=3.58$, $p<.001$). As has always been found in previous research, within each condition, utilization of relevant dimension information was higher than utilization of relevant configural information even though they were of the same validity.

Table 2
Subjects' Mean Utilizations from the First Experiment

	condition		
	configural indicator	control with cue 1 relevant	control with cue 2 relevant
cue 1	.16	.21	-
cue 2	.16	-	.11
cue 3 interacting with cue 1	.11	.04	-
cue 3 interacting with cue 2	.11	-	.07

As we hypothesized, the relevant configural information was more highly utilized in the configural indicator condition than in either control condition. It should be noted that, in the environments, the validity of the configural information is the same in the configural indicator condition as in the control conditions. Subjects more strongly utilized the dimensional information in the configural indicator condition than in one control condition, but that was reversed for the other control condition.

The stimuli used in the present study had been previously found to produce equal utilization when relevant; however, that was in environments where only one dimension was relevant and there was no relevant configural information. Hence, we must conclude that in more complex environments, the effects due to the physical representation of the stimuli, salience, are more complex. It was also shown that this extends to patterns of the stimuli acting in a configural manner. In comparing the two control conditions, it is seen that the interaction of dimension 3 on dimension 2 was more strongly utilized than the interaction of dimension 3 on dimension 1. It is most interesting that in the configural indicator condition these salience effects did not appear; the utilization of the two relevant cue dimensions was the same. Also the utilization of the interaction of cue dimension 3 on cue dimension 1 was the same as the utilization of the interaction of cue dimension 3 on cue dimension 2.

Models

There are two models that attempt to explain behavior in this research paradigm. We now explore each of these models and how well each can account for the present findings.

Hypothesis Generation

Castellan and Edgell (1973) proposed a hypothesis generation model in which, on each trial, the subject forms a hypothesis of whether or not paying attention to a particular item of information will lead to a correct answer. The model proposes that the subject entertained hypotheses for paying attention to the event base rate (i.e., ignoring the cues), for each cue dimension, and for each pattern of cue dimensions. That is, on each trial the subject would hypothesize with some probability (which is a model parameter) that paying attention to the event base rate would lead to a correct answer and with one minus that probability that paying attention to the event base rate would not lead to a correct answer. In that same way, with a different probability, the subject would generate one or the other hypothesis for paying attention to the first dimension. This process would continue for each cue dimension and each pattern of cue dimensions. If the subject generated one and only one expectation of making a correct answer, then the subject would pay attention to the corresponding item of information on that trial. In any other case, the subject would generate a new set of hypotheses according to the same probabilities until reaching the state where one and only one expectation is positive. The model was proposed in two versions, but only the second is being considered here because it was found to fit better (Castellan & Edgell, 1973) and because the first version of the model predicts that subjects are unable to utilize relevant configural information. There is much evidence that subjects can and do utilize relevant configural information (e.g., Edgell & Castellan, 1973; Edgell, 1978; Edgell, 1980; Estes, 1972; Stockburger & Erickson, 1974).

The model further postulates that after the subject chooses which information to pay attention to, the value of that information on this trial is observed by the subject. Then, conditional on the value of the information, expectations are generated as to whether each of the two responses will be correct or not. Again, these expectations are generated with probabilities that are parameters of the model. The subject, as before, generates sets of hypotheses until one and only one response is expected to be correct. The subject then makes this response.

Castellan and Edgell (1973) proposed that the model parameter values (the probabilities of expecting to be correct if a particular item of information is used and the probabilities of expecting to be correct if a particular response is made to the observed value of the item of information that was chosen to be observed) would be adjusted through learning trial by trial. Although the mechanism of this adjustment was never specified, asymptotic values were hypothesized. These asymptotic values are those that would result from optimal use of the information by the subject. Because these values are functions of the environment probabilities, no model parameters are estimated from subjects' data. Equations derived in Castellan and Edgell (1973) were used to calculate predicted response proportions for the environments in the study reported here. These predicted response proportions were then transformed to predicted utilization weights in the same manner as the subjects' response proportions were transformed to utilization weights.

The mean asymptotic utilization weights as predicted by this model are given in Table 3. As the model makes no different predictions depending on the representation of the cue, and thus predicts the same for each cue dimension and each interaction, Table 3 combines each into "dimensional information" and "configural information." Comparing the values in Table 3 to those in Table 2, it is seen that this model fits the basic finding. The predicted data values are generally in line with those found. This is notable especially considering that no parameters were estimated from the subjects' data. The Hypothesis Generation Model correctly predicts that the configural utilization will be higher with the configural indicator than in the control conditions. The model has no ability to differentiate between different representations of the cues. Thus it cannot predict the various differences found due to salience.

Table 3
Mean Utilizations Predicted by the Hypothesis Generation Model

	condition	
	configural indicator	control
dimensional information	.18	.21
configural information	.12	.09

RASHNL

Kruschke and Johansen (1999) proposed a connectionist learning model, RASHNL, to account for behavior in this paradigm. The model is an extension of an earlier model, ALCOVE (Kruschke, 1992). RASHNL added limited-capacity attention that rapidly shifts and a learning mechanism for the distribution of these shifts. The model has nine free parameters, including a salience parameter for each of the three cue dimensions. These parameters must be estimated from the subjects' data. We fit RASHNL to the results of the first experiment using STEPIT (Chandler, 1969). Because RASHNL is a learning model, simulations must be used to estimate its predictions. We ran 500 simulated subjects for each of the three conditions in the first experiment for each estimate of the predictions of RASHNL. For fitting the model, error was defined as the sum of squared error between the model's predictions and the subjects' means. Only utilization weights from relevant dimensions and patterns were used in the error calculation. Therefore, it is assumed that a mean utilization of an irrelevant dimension or pattern different from 0 for either actual subjects or model simulated subjects reflects only error variance.

Recall that Edgell et al. (1992) found equal utilization for each of the cue dimensions that were used in the present studies when only that cue dimension was relevant. To account for that finding the salience parameters of RASHNL would have to be of the same value. Kruschke and

Johansen (1999) point out that the relative value of the salience parameters affects RASHNL's predictions, not the absolute size of them. Because the physical representation of the cue dimensions was the same in the present studies as in the Edgell et al. (1992) studies, the same salience parameter values that fit one study must also fit the other. We fit the model by setting the three salience parameters to 1.0 and holding them constant. The predictions of the best fit are given in Table 4. As seen there, the fit is not good. Indeed, the best that the model could do is to predict the same level of configural utilization in the configural indicator condition as in the control conditions. No values of the other parameters could be found that gave a higher utilization of the configural information for the configural indicator condition than for the control conditions. However, values of the parameters could be found that gave the opposite result. Both these predictions are contrary to the results of the present experiment. If the salience parameters are allowed to be unequal and adjusted in fitting the model, then RASHNL can predict the correct direction of the difference in configural utilization. Of course, then it will not fit the results of Edgell et al. (1992).

Table 4
Mean Utilizations Predicted by RASHNL

	condition	
	configural indicator	control
dimensional information	.12	.14
configural information	.11	.11

Extension and Replication

The configural indicator dimension was the size of the stimuli. Perhaps there is something inherent in the size of the stimuli that makes it possible for subjects to use that dimension as a configural indicator when it acts as such in the environment. To verify the generalizability of the results, the conditions with each of the other two dimensions serving as the configural indicator were run. The appropriate two control conditions were also run for each configural indicator condition. The condition, previously run, with size as the configural indicator and the two control condition were also run to replicate the earlier findings.

Method

Subjects. The subjects were 407 students in introductory psychology who participated to satisfy a course requirement. At first we were only intending on running 6 conditions: the color dimension as the configural indicator along with its two control conditions and the shape dimension as the configural indicator along with its two control conditions. We randomly assigned the first 128 subjects to these 6 conditions. Twice as many subjects were randomly assigned to the configural indicator conditions as to each control condition. However, it seemed advisable to include the previously run condition with shape as the configural indicator and the two associated control conditions as a replication. The next 279 subjects were randomly assigned to these 9 conditions. All subjects came from the same pool. Even if there was a difference between earlier and later subjects, this would not affect the validity of the study because the only comparison is between each configural indicator condition and its two control conditions. Subjects were randomly assigned between those conditions.

Apparatus. The apparatus was the same as in the first experiment.

Procedure. The procedure was the same as the first experiment.

Results and Discussion

Again, learning curves confirmed that subjects had reached asymptote by the last trial block. In the same manner as in the first experiment, utilization weights were calculated for each subject from the last block of trials. Mean asymptotic utilization weights are presented in Table 5.

Table 5
Subjects' Mean Utilizations for the Replication and Extension

cue 1 as configural indicator

	condition: configural indicator	control with cue 2 relevant	control with cue 3 relevant
cue 2	.18	.18	-
cue 3	.13	-	.13
cue 1 interacting with 2	.13	.07	-
cue 1 interacting with 3	.10	-	.06

cue 2 as configural indicator

	condition: configural indicator	control with cue 1 relevant	control with cue 3 relevant
cue 1	.21	.19	-
cue 3	.14	-	.11
cue 2 interacting with 1	.15	.09	-
cue 2 interacting with 3	.11	-	.05

cue 3 as configural indicator

	condition: configural indicator	control with cue 1 relevant	control with cue 2 relevant
cue 1	.19	.18	-
cue 2	.15	-	.17
cue 3 interacting with 1	.12	.05	-
cue 3 interacting with 2	.12	-	.09

The mean configural use is again higher in each configural indicator condition than in the corresponding control conditions. The difference is significant in each case except one: cue 1 interacting with 2 ($t(108)=2.829$, $p=.006$), cue 1 interacting with 3 ($t(107)=2.187$, $p=.031$), cue 2 interacting with 1 ($t(108)=2.733$, $p=.007$), cue 2 interacting with 3 ($t(110)=2.968$, $p=.004$), cue 3 interacting with 1 ($t(58)=3.519$, $p=.001$), and cue 3 interacting with 2 ($t(61)=1.374$, $p=.174$).

This difference for cue 3 interacting with 2, however, was found to be significant in the first experiment. The effect size was smaller for this interaction in both experiments. The lack of significance in the present experiment is due to the smaller number of subjects and thus is of no consequence. It should be noted that the difference found in the two experiments is in the same direction and nearly the same size.

Unlike in the first experiment, in the replication of the configural indicator condition with dimension 3 acting as the configural indicator, there was a difference in the utilization of the two relevant cue dimensions ($t(29)=2.291$, $p=.029$). Indeed, across the 9 conditions there were many differences in utilization levels both for relevant cue dimensions and for relevant configural information. No consistent pattern in these differences emerges. Thus, it must be concluded that the effects of salience are complex in environments with more than one dimension relevant and with relevant configural information. However, one conclusion does hold consistently: When a dimension acts as a configural indicator on two other dimensions, the utilization is higher than when that dimension acts configurally on a single other dimension.

Extension with Separable Stimuli

Recall that Edgell and Morrissey (1992) found that using stimuli that create a unitary whole for the cues greatly facilitates the use of configural information over cue dimensions that are separated. The experiments presented so far have all used unitary stimuli. For completeness, we ran an experiment where the stimuli are separable. Although expecting configural utilization to be lower, it is interesting to know if it will still be higher when the configural cue acts as a configural indicator.

Method

Subjects. The subjects were 96 students in introductory psychology who participated to satisfy a course requirement.

Apparatus. The apparatus was the same as in the first experiment.

Procedure. The stimuli representations for the cues were: cue1 stuffy nose or runny nose, cue 2 diarrhea or constipation, and cue 3 fever or chills. Other than that the environment, the three conditions and all the other procedure was the same as the first experiment.

Results and Discussion

Again, learning curves confirmed that subjects had reached asymptote by the last trial block. In the same manner as in the first experiment, utilization weights were calculated for each subject from the last block of trials. Mean asymptotic utilization weights are presented in Table 6.

Table 6
Subjects' Mean Utilizations from the Separable Stimuli Experiment

	condition		
	configural indicator	control with cue 1 relevant	control with cue 2 relevant
cue 1	.06	.08	-
cue 2	.15	-	.13
cue 3 interacting with cue 1	.00	.00	-
cue 3 interacting with cue 2	.03	-	.03

As can be seen from Table 6, there was little if any utilization of the configural information. Cue 2 received the highest utilization. It should be noticed that Edgell and Morrissey (1992) found some although less configural utilization in an environment where the relevant configural information was a relevant pattern of two of the three cues with the third cue also relevant. The present environments are more complex. Also, it is obvious that cue 2 was more salient than cue 1. Salience differences may have interfered with configural utilization. Salience effects on the utilization of relevant configural information warrants further investigation. There was no evidence of a facilitating effect for a configural indicator when the stimuli are separable. This also warrants investigation.

Conclusion

The results of our experiments with unitary stimuli supported the hypothesis that configural information utilization is facilitated in environments in which one cue provides an indication of which of two other cues is relevant to the decision. As we suggested earlier, such complex environments likely are the rule rather than the exception in real-world situations in which information is presented to decision makers, and that information is used to guide the search for other pieces of information. The concept of a configural indicator has much in common with decision trees. In a decision tree the observed outcome at one stage selects which path one pursues and thus which outcome is observed next. Decision trees are often prescribed as a decision aid, which supports our view that they, and therefore also configural indicators, are common and familiar.

The Hypothesis Generation Model predicted the general direction of the results. However, as this model has no mechanism to account for the complex differences found due to salience effects it cannot completely account for the results. If parameter values (equal salience parameters) that would allow RASHNL to account for earlier findings are used, then that model cannot account for the present general findings. If the salience parameters are allowed to vary, then RASHNL can account for the present general findings of higher configural utilization in a configural indicator condition, but will fail to account for the previous findings. Even in that case, it will not account for the complex differences due to salience that were found in the present studies. Using values of the salience parameters that produces higher utilization for one configural indicator condition will not produce higher utilization in the other configural indicator conditions. The parameter values cannot be allowed to vary between conditions since the differences between conditions must arise from learning. This is a fundamental failure of the RASHNL model to account for these findings.

Effects of the salience of representation of the stimuli were large. Indeed salience effects have shown up in much previous research, but have been ignored by other researchers. Edgell, Bright, Ng, Noonan, and Ford (1992) performed several experiments searching for three cues with the same salience, such that subjects would show the same level of utilization for the cue that was relevant in environments where only one cue was relevant. They tried several representations, and found several to show highly different levels of utilization, thereby implying they had different saliencies. The three representations that they did find to have equal saliencies in one cue relevant environments, showed good size salience effects with more complex environments in the present experiments. The effect of salience for different cue representations is a major confound with studies using nonmetric multiple-cue probability learning. It needs much further study.

References

Castellan, N.J., Jr. (1973). Multiple-cue probability learning with irrelevant cues. *Organizational Behavior and Human Performance, 9*, 16-29.

Castellan, N. J., Jr. (1977). Decision making with multiple probabilistic cues. In N. J. Castellan, Jr., D. B. Pisoni, & G.R. Potts (Eds.), *Cognitive theory* Vol II (pp. 117-147). New Jersey: L. Erlbaum.

Castellan, N. J., Jr., & Edgell, S. E. (1973). An hypothesis generation model for judgment in non-metric multiple-cue probability learning. *Journal of Mathematical Psychology, 10*, 204-222.

Chandler, J.P. (1969). STEPIT-Finds local minima of a smooth function of several parameters. *Behavioral Science, 14,* 81-82.

Edgell, S. E. (1978). Configural information processing in two-cue probability learning. *Organizational Behavior and Human Performance*, *22*, 406-416.

Edgell, S. E. (1980). Higher order configural processing in nonmetric multiple-cue probability learning. *Organizational Behavior and Human Performance*, *25*, 1-14.

Edgell, S. E. (1993). Using configural and dimensional information. In N. J. Castellan, Jr. (Ed.), *Current issues in individual and group decision making* (pp. 43-64). Hillsdale, NJ: Erlbaum.

Edgell, S.E., Bright, R.D., Ng, P.C., Noonan, T.K., & Ford, L.A. (1992). The effects of representation on the processing of probabilistic information. In B. Burns (Ed.), *Percepts, concepts, and categories: The representation and processing of information* (pp. 569-601). New York: Elsevier.

Edgell, S. E., & Castellan, N. J., Jr. (1973). The configural effect in multiple-cue probability learning. *Journal of Experimental Psychology*, *100*, 310-314.

Edgell, S.E., Castellan, N.J., Jr., Roe, R.M., Barnes, J.M., Ng, P.C., Bright, R.D., & Ford, L.A. (1996). Irrelevant information in probabilistic categorization. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 22,* 1463-1481.

Edgell, S.E., & Morrissey, J.M. (1992). Separable and unitary stimuli in nonmetric multiple-cue probability learning. *Organizational Behavior and Human Decision Processes, 51*, 118-132.

Edgell, S.E., & Roe, R.M. (1995). Dimensional information facilitates the utilization of configural information: A test of the Castellan-Edgell and the Gluck-Bower models. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 21*, 1495-1508.

Estes, W. K. (1972). Elements and patterns in diagnostic discrimination learning. *Transactions of the New York Academy of Sciences*, *34*, 84-95.

Goldberg, L.R. (1968). Simple models or simple processes: Some research on clinical judgments. *American Psychologist, 23,* 483-496.

Kruschke, J. K. (1992). ALCOVE: An exemplar-based connectionist model of category learning. *Psychological Review*, *99*, 22-44.

Kruschke, J.K., & Johansen, M.K. (1999). A model of probabilistic category learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 25*, 1083-1119.

Meehl, P.E. (1954). *Clinical versus statistical prediction.* Minneapolis: University of Minnesota Press.

Stockburger, D. W., & Erickson, J. R. (1974). Probabilistic discrimination learning with dimensionalized stimuli. *Organizational Behavior and Human Performance*, *11*, 157-171.

Appendix

Validity and Utilization Measures

An environment such as used in the present studies can be thought of as being analogous to a completely crossed factorial design experiment. The cue dimensions are the factors. The events or the responses are the dependent measures. Since there are only two event values in the environments used here, we can code them arbitrarily. If we choose zero and one, then the event conditional probabilities or the response proportions would be the cell means in this analogy. We can now apply the standard analysis of variance (ANOVA) linear model used to model the means of such experiments to the conditional probabilities and to the response proportions. (It should be noted that this is straightforward if the probability of each cue pattern is equally likely, as it is in the present experiments. If not, the problem becomes more complex analogously to the unequal N case in ANOVA.) Just as the linear model transforms means to main effects and interactions, it transforms event conditional probabilities (response proportions) to measures of the validity (utilization) of each cue dimension and of the configural information for each pattern.

To better see this, consider a two dimension environment as an example. The linear model for the environment is given by:

$$P(E_1|C_{1,i}C_{2,j}) = \mu + \alpha_i + \beta_j + \gamma_{i,j} \quad (i,j = 1,2).$$

Adding the usual conditions that all model parameters sum to zero over any subscript makes the parameters estimable. The alpha term gives the validity of dimension 1, the beta term gives the validity of dimension 2, and the gamma term gives the validity of the configural information in the pattern. For each parameter all the values are equal except for sign. Without loss of generality, we choose the positive one as the measure to use. The validities range from 0, which implies no validity, to .5, which implies total dependence of the event on this cue dimension or pattern. Replacing the event conditional probabilities with response proportions on the left side of the equation would produce analogous utilization measures. It should be noted that one cannot arbitrarily choose the positive parameter values, but one must choose the same parameters as chosen for the environment. A negative value indicates that the subject is utilizing that information in the opposite direction from the environment. Other than sign, the range and interpretation of the values are exactly the same as for the validities. This makes comparison of a subject's utilizations with the environment's validities very easy.

It should be noted that this transformation to the linear model terms is a nonsingular linear transformation. To further illustrate this, the transformation for the two dimension example can be given by the following matrix equation:

$$\begin{bmatrix} V_0 \\ V_1 \\ V_2 \\ V_{1,2} \end{bmatrix} = \begin{bmatrix} 0.25 & 0.25 & 0.25 & 0.25 \\ 0.25 & -0.25 & 0.25 & -0.25 \\ 0.25 & 0.25 & -0.25 & -0.25 \\ 0.25 & -0.25 & -0.25 & 0.25 \end{bmatrix} \begin{bmatrix} P(E_1|C_{1,1}C_{2,1}) \\ P(E_1|C_{1,2}C_{2,1}) \\ P(E_1|C_{1,1}C_{2,2}) \\ P(E_1|C_{1,2}C_{2,2}) \end{bmatrix}$$

The vector on the left of the equal sign contains the validities of the event base rate (mu above), cue dimension 1 (alpha), cue dimension 2 (beta), and the configural information in the pattern (gamma), respectively. Replacing the event conditional probabilities in the vector on the right with response proportions would give utilization measures. The values in the rows of the transformation matrix should be familiar as the normed standard planned comparison coefficients for the grand mean, factor 1, factor 2, and the interaction, respectively. (Positive and negative signs can be swapped in each row if necessary to make the validity positive, just as the positive term was chosen above.) The same transformation matrix can then be used to transform a subject's response proportions into utilization weights. This example is easily expanded to the case of three binary valued dimensions such as were used in the present experiments.