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REPORT OF THE 1976-77 COMMITTEE ON HUMAN INFORMATION PROCESSING

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1. Introduction

Accountants are interested in decision making in their roles as both providers and users of information. As providers, accountants supply information to external parties for use in investment portfolio determination, credit-granting, and other types of decisions, and to internal parties for use in decisions concerning production, pricing, capital expenditures, and other areas of management. As users, accountants may take a more active role in decision making than that of simply providing information; they may be asked to choose the types of information to be used and/or to actually make decisions based on that information. Moreover, decisions made by accountants may impact the costs of producing alternative information sets as well as the costs incurred by individuals to process that information. Auditors are required to integrate various pieces of information in making decisions concerning internal control systems, substantive testing procedures, sufficiency of evidential matter, fairness of statement presentation, and so on.

The primary reason for accountants' interest in decision making is the potential for improving the quality of decisions. Three basic strategies exist for improving human decisions: (1) The information set upon which such decisions are based may be altered. This alternative

In Section 5 of the report, we indicate briefly how the principal research approaches can be integrated into a modified information economics framework. Section 6 compares and contrasts several important characteristics of those approaches which have received major attention in the accounting literature. Finally, Section 7 suggests various directions for human information processing research, based upon a multi-paradigm research approach.

2. Information Processing and Decision Making Given Uncertainty

Consider situations such as a loan officer evaluating possible loan outcomes (perhaps default or no default on a prospective commitment), a security analyst considering possible returns for an investment portfolio, or an auditor assessing possible market values for inventory items when a substantial write-down of historical cost values is being contemplated. In all these situations, an individual generates relative likelihoods of possible outcomes of a judgment variable, based on financial information. Information processing research concentrates on various aspects and determinants of these judgment processes.

To describe such situations more precisely, define y_j to be the j'th (standardized) value of a financial variable of interest such as possible loan outcomes or portfolio returns.[3] Define $P(y_j)$ to be

[3]Upper and lower case letters respectively signify raw and standardized values of random variables. Also, an upper or lower case letter with a bar underneath denotes a matrix, and a tilde (~) denotes a random variable.

the (prior) subjective probability of event j ($j = 1,2,\ldots,J$) for random variable $\tilde{y}$ for a single decision maker. The $P(\tilde{y})$ distribution reflects the individual's available information and experience, and the distribution is generated prior to the receipt of any new information. The set $\{y_i\}$ should be a mutually exclusive, exhaustive partition of the event space, and the number of events (i.e., J) is specified by the individual given the situation. The normative interpretation of $P(\cdot)$ is that it is a function depicting the internally consistent beliefs of a rational individual with "infinite" information processing ability and is based on the information available to the individual at a point in time (Savage, 1954).[4] Treatment of quantified subjective beliefs as probabilities requires that $P(\cdot)$ satisfy the conditions of a probability measure (see Wright, 1977c).

An individual's prior distribution reflects all information previously utilized by the individual. The loan officer or security analyst may seek additional information before deciding whether to implement an action. After the additional information (e.g., financial statements or other accounting reports) is obtained, the individual will reconsider his initial $P(y_j)$ assessments. Specify the newly obtained information signal x_k to be a realization of random variable $\tilde{x}_k$. Then

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[4] "It is important to keep clear the distinction between the somewhat idealized consistent personal probabilities that are the subject of this paper and the usually inconsistent subjective probabilities that can be inferred from real human choices among bets, and the words 'personal' and 'subjective' here help do so" (Edwards, Lindman and Savage, 1963, p. 197).

the revision of $P(y_i)$ to a new (posterior) set of beliefs $P(y_j|x_k)$ is accomplished through cognitive information processing. Any number of processes might be used to move from $P(y_j)$ to $P(y_j|x_k)$ (see Wright (1977a) for a review); however the conditional (posterior) probability assessments generated as a result of the individual's processing the new datum should be consistent with Bayes' Rule if subjective probability assessments are to be internally consistent, since Bayes' Rule is a logical consequence of conditional probabilities (see, e.g., DeGroot, 1970, pp. 11-12).

Bayes' Rule implies that the result of an information-processing model based on new information $\tilde{x}_k = x_k$ should be a revision of beliefs such that

$$P(y_j|x_k) = \frac{P(x_k|y_j)P(y_j)}{\sum_{j=1}^{J} P(x_k|y_j)P(y_j)}, \qquad (1)$$

where $\sum_{j=1}^{J} P(x_k|y_j)P(y_j) = P(x_k) > 0$. The posterior $P(y_j|x_k)$ becomes the prior probability for any subsequent revision of beliefs if the individual chooses to obtain additional information. Notice that individuals must generate (or imply) conditional x_k likelihoods $P(x_k|y_j)$ (or process information <u>as</u> <u>if</u> they were generating the data likelihoods) to arrive at the posterior probabilities $P(y_j|x_k)$. The $P(x_k|y_j)$ indicate the relevance of information variable x_k in changing $P(y_j)$ to $P(y_j|x_k)$ for event j ($j=1, 2, \ldots, J$). The posterior distribution $P(\tilde{y}|x_k)$ represents the degree of uncertainty which exists in the

mind of the individual at a specific point in time concerning, e.g., what may happen to the loan or what return might be obtained on an investment portfolio.

The perspective provided by Brunswik's "probabilistic functionalism" (Brunswik, 1952; Postman and Tolman, 1959) also recognizes the inconclusive or probabilistic nature of information used in decision making. The Brunswikian formulation of judgment under uncertainty is similar to the Bayesian formulation in that both paradigms rely on the posterior distributions $P(\tilde{y}|x_k)$ to infer certain aspects and results (e.g., accuracy, reliability) of cognitive information processing models. However, a characteristic not always fully appreciated by researchers using the lens model is that a single fractile of the $P(\tilde{y}|\underline{x})$ distribution (e.g., the most likely y_j outcome) is obtained from subjects (where $\underline{x}$ is a $K \times 1$ vector) for multiple stimuli (situations) where the K x_k's for each stimulus are usually presented simultaneously. Bayesian studies typically require subjects to describe $P(\tilde{y}|\underline{x})$ distributions more completely with direct (or implied) probability assessments for $J > 1$ events, perhaps with only one stimulus being used. The x_k's usually are provided sequentially to the subject and the $P(\tilde{y}|x_K, x_{K-1}, \ldots, x_1)$ distributions are studied as a series.

Descriptions and determinants of cognitive processes for revising $P(\tilde{y})$ to $P(\tilde{y}|\underline{x})$ have been discussed in the accounting-related human information processing literature. Several heuristic cognitive processes have been described by Swieringa, et al. (1976) and Wright

(1977a). The cognitive style literature, e.g., Barrett et al. (1976), Barrett (1977), Driver and Mock (1975), Mock and Vasarhelyi (1976), suggests that psychological characteristics may determine the type of probability-revision process selected by individuals, including the amount and complexity of data utilized (also see Bariff and Lusk, 1974). The human information processing literature in psychology implies that situational conditions, alternative judgment tasks, properties of data sets, and experience may affect the choice of a revision process for $P(\tilde{y})$ (c.f., Slovic and Lichtenstein, 1971).

An additional dimension to human information processing research is provided by the process tracing approach. The aim of process tracing, according to Newell and Simon (1972) and Payne (1976), is to better understand the informational and judgmental processes occurring between the introduction of stimulus cues and a final choice. This approach to the study of human information processing typically is suggested as an alternative to input/output descriptive modeling, i.e., Bayesian or lens model approaches, which represent cognitive thought processes by a mathematical function.

3. Information Processing Research Approaches Used by Accountants

3.1. The Bayesian Approach. The typical Bayesian judgment study first requires subjects to generate (or accept as given) a probability distribution over a (relatively small) number of prespecified

values (or categories) of $\tilde{y}$.[5] This initial distribution reflects all previously known information and is prior to any new information provided by the experimenter. Data are then provided to the subjects, and revised (posterior) relative likelihood assessments (perhaps in the form of odds) are obtained from the individuals. The data-conditional posterior assessments generated as a result of individual i's usage of a cognitive processing procedure (i.e., a cognitive "heuristic") based on the inconclusive data should be consistent with Bayes' Rule if subjective probability assessments are to be internally consistent, and this has been the major research question in several studies.

The subjective probability distribution approach offers the likelihood measure, $P(x_k|y_j)$, as an indication of the relevance that a particular x_k has for changing $P(y_j)$ to $P(y_j|x_k)$ for event j. To directly compare the relative likelihood of events y_j and y_j' and the data diagnosticity of datum x_k, one may form the ratio of two posterior probabilities yielding

$$\frac{P(y_j|x_k)}{P(y_j'|x_k)} = \frac{P(x_k|y_j)P(y_j)}{P(x_k|y_j')P(y_j')}, \quad j \neq j' \qquad (2)$$

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[5]If the Bayesian researcher is willing to design more complex experiments, and to incur a greater computational burden, continuously varying data and a continuous set of hypotheses can be handled in the Bayesian approach (for formulae, see Schlaifer (1959) or Winkler (1972); for examples of Bayesian research using continuous distributions, see DuCharme and Peterson (1968) and Peterson and Phillips (1966).

Rule. The degree of conservatism is usually dependent on properties of the response mode and the data, particularly the magnitude of likelihood ratios and the number of data observations provided.

Three generalized explanations for conservatism (at least in laboratory settings) have been generated (Edwards, 1968; Slovic and Lichtenstein, 1971, pp. 693-698). The three main hypotheses are: (1) People misperceive the conditional environmental distributions $\hat{\phi}(\tilde{x}_k|y_j)$ (particularly for extremely unlikely events), and perhaps they misperceive more general properties of the process generating the $\tilde{x}_k$ (Rapoport and Wallsten, 1972, p. 159); (2) People have great difficulty aggregating the diagnostic impact of multiple x_k, i.e., they do not combine likelihood ratios very well (Edwards, 1968, p. 18), and (3) A form of response bias explains the conservatism evidence in that people exhibit conservatism only for very extreme posterior y_j odds (DuCharme, 1970) and/or individuals generally resist indicating extremely high or low assessments, i.e., a type of floor/ceiling effect biases probability indications.

As an important aside, research on subjective probability elicitation methods has developed rapidly in recent years. Two basic response methods have been used: (1) obtaining direct assessments in the form of probabilities or odds and (2) behavioral choices from which probabilities may be inferred, such as selection among lotteries or bets.[7] Generally, elicitation of odds rather than probabilities is

[7]Winkler (1972, Ch. 2) exposits the two methods. Slovic and Lichtenstein (1971, pp. 698-699) review empirical results.

desirable (mainly to avoid floor and ceiling effects) if direct assessments are to be obtained. Behavioral elicitation methods require more complicated experimental procedures; however, the inferred probabilities are actually based on choices among alternative gambles.

3.2. The Lens Model Approach. Brunswik (1952, 1956) proposed the lens model paradigm to provide for explicit recognition of the interdependence between environmental and individual-specific variables. Important methodological extensions of the model have been provided by Castellan (1972, 1973), Dudycha and Naylor (1966), Hammond, Hursch, and Todd (1964), Hursch, Hammond, and Hursch (1964), Stewart (1976), and Tucker (1964).

The lens model paradigm emphasizes the symmetry between the environmental and subject response sides of the model. Given realizations of K information cues (random variables) for each of N stimuli, the result is a $N \times K$ cue matrix, $\underline{X}$. Realizations of the environmental random variable, $\tilde{y}_e$, are typically available yielding a $N \times 1$ vector $\underline{y}_e$.[8,9] Subject i's judgments (predictions, evaluations), conditional on $\underline{X}$, yield a $N \times 1$ vector $\underline{y}_i$. The $\underline{X}$ matrix and the $\underline{y}_e$ outcomes plus the subject judgment vectors $\underline{y}_i$ (i=1, 2, ..., I) provide the basic data for a lens model study.

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[8]By employing canonical analysis, the univariate lens model can easily be extended to the case where y_e and y_i become multidimensional variables (see, e.g., Castellan, 1972).

[9]Ashton (1974c, 1976b) and Casey (1976) discuss the potential problem of not being able to observe criterion outcomes in accounting decision situations.

Within the regression or discriminant analysis operationalization of the lens model (see, e.g., Wright (1977b) and Libby (1975), respectively) the cues may take on continuous sets of values, and the cue-criterion relationships, as well as cue intercorrelations, may reflect environmental data relationships.[10] Assuming standardized variables, multiple regression analysis may be utilized to derive the following (least-squares optimal) linear predictions:

$$\hat{y}_{en} = \hat{\beta}_{1e}x_{1n} + \hat{\beta}_{2e}x_{2n} + \cdots + \hat{\beta}_{ke}x_{kn} \tag{7}$$

$$\hat{y}_{in} = \hat{\beta}_{1i}x_{1n} + \hat{\beta}_{2i}x_{2n} + \cdots + \hat{\beta}_{ki}x_{kn} \tag{8}$$

where $\hat{\underline{y}}_e$ is the vector of N (linear) estimates of the $\underline{y}_e$ values (given $\hat{\underline{\beta}}_e$) and $\hat{\underline{y}}_i$ is the vector of N estimated responses to x (standardized $\underline{X}$) for subject i. The number of judgments obtained is determined by stability conditions required for the linear multiple regression models which describe each side of the lens and the context of the study. The estimated multiple correlation coefficient R_e $(= r_{y_e\hat{y}_e})$ describes the extent of the linear relationship between the predictions of the environmental model and the actual y_e. $R_i (= r_{y_i\hat{y}_i})$ indicates the linear predictability of a subject's judgments, based upon an additive (compensatory) linear model.[11] The vectors of beta weights, $\hat{\underline{\beta}}_e$ and $\hat{\underline{\beta}}_i$, provide

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[10]When the lens model is operationalized via analysis-of-variance, e.g., Ashton (1974a, 1974b), discrete or categorical values are generally used, especially if the researcher wishes to include a full (or a substantial fractional) replication of cue value combinations.

[11]Alternative functional forms can be postulated (e.g., see Einhorn (1970, 1971) and P. Wright (1974b).)

some indication of the relative importance of the cues in the environment and for the subject, respectively.[12] The degree of relevance for cue x_k($k=1, 2, \ldots, K$) in the environment is measured by the product-moment correlation r_{ek}, and r_{ik} measures the degree of relevance of cue x_k for subject i's judgments. The correlations $r_{kk'}$($k \neq k'$) represent the degree of scaled covariance between cues x_k and $x_{k'}$.

Nonlinear cue dependence within the lens model framework is indicated by the correlation between the residuals from the environmental model (Equation 7) and the residuals from the subject judgment models (Equation 8). The correlation between the vectors of residuals (labeled r_e^i) is the partial correlation between $\underline{y}_e$ and $\underline{y}_i$ exclusive of the linear relationships shared with $\underline{x}$. If there is only a random correspondence between the residuals or if a subject employs a nonlinear model which is sufficiently different from the nonlinear relationships on the environment side of the lens (given an allowance for sampling error), a (near) zero correlation coefficient may be obtained (Hursch, Hammond, and Hursch (1964, p. 47), Einhorn (1970, p. 223)). The precise nature of nonlinear cue usage will not be indicated by this simple association test.

The performance measure used in the typical lens model study is $r_a^i(\equiv r_{y_e y_i})$ which is referred to as the achievement index for subject i. Notice that since the lens model is essentially a multidimensional

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[12]The desirability of using regression coefficients (or correlations) as indicators of importance depends on the number of observations relative to the number of cues and the collinearity among cues.

Driver and Streufert (1967)[13] who hypothesized, and presented evidence, that a decision maker's level of information processing (i.e., his cognitive complexity) is a quadratic (inverted U-shaped) function of the level of environmental complexity with which he is faced. In other words, level of information processing increases with increases in environmental complexity, but only up to a point. Then, level of information processing decreases with increased levels of environmental complexity. Environmental complexity is defined as the aggregate effect of information complexity (loosely defined as the quantity of information that impinges upon the decision maker per unit of time), noxity (degree of increase in negative feeling due to the input), and eucity (degree of increase in positive feeling due to the input) (Driver and Mock, 1975). In accounting contexts the focus has been almost entirely on information load. The dependent variable, level of information processing, reflects two basic features of a decision maker's cognitive structure--(1) differentiation (the number of dimensions taken into account when formulating a decision), and (2) integration (the nature of the rules used to combine these dimensions in arriving at a decision) (Miller and Gordon, 1975).

To a large extent, cognitive-complexity research has been concerned with locating decision makers at particular points on particular

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[13]Several psychologists had conducted research on cognitive complexity prior to the appearance of Schroder, Driver and Streufert (1967). Examples are Bieri (1955), Kelly (1955), Scott (1962, 1963), Crockett (1965), and Vannoy (1965).

inverted U curves. For example, whether some ("abstract") decision makers reach higher levels of information processing than other ("concrete") decision makers, and whether different decision makers reach their highest level of information processing at the same, or at different, levels of environmental complexity. Another issue considered is that while the point (of level of information processing) at which a decision maker is located on a particular inverted U curve is largely a product of the immediate information environment (called "conditional" factors), the overall level of that curve is determined, in part, by the long-run training characteristics of the environment (called "dispositional" factors). Thus, there is some indication that informational environments reflecting a certain (intermediate) level of diversity and conflict can have the long-run effect of increasing a decision maker's level of information processing (Miller and Gordon, 1975).

Recently, cognitive complexity research has focused on problem-solving approaches used by decision makers. For example, Driver (see Driver and Mock, 1975) has posited two dimensions of information processing--(1) amount of information used (consisting of a "minimal" data user and a "maximal" data user), and (2) degree of focus in the use of data (those who see all data as leading to one solution versus those who see data as having varied meanings). These two dimensions are combined into five "decision styles," one of which is a combination of two others. Another example is research on field independence/dependence,

a construct developed by Witkin and his associates (e.g., Witkin, Dyk, Patterson, Goodenough and Karp, 1962). Lusk (1973) and Doktor and Hamilton (1973) have used this construct in accounting and management research contexts. Field independence/dependence is defined as an analytical versus a global way of perceiving, and it focuses on the decision maker's tendency, or lack thereof, to experience items as discrete from their backgrounds, i.e., the ability to overcome the influence of an embedding context (Benbasat and Taylor, 1976, p. 13).

Cognitive complexity research suffers to some extent from several unresolved methodological and conceptual issues, including the nature and measurement of "environmental complexity," "level of information processing," and "decision styles," the generality and multidimensionality of the constructs, the role of relevant versus irrelevant information, and the link, if any, between level of information processing (or decision styles) and performance. See Barrett et al. (1976), Benbasat and Taylor (1976) and Snowball (1976).

3.3.2. Cognitive Styles. Cognitive styles research has grown out of the early work by Jung, who suggested that individuals may be classified according to their predominant modes of perceiving and evaluating objects. Jung's viewpoint has been operationalized via a personality assessment inventory known as the "Myers-Briggs Type Indicator" (Myers, 1962), which attempts to categorize individuals along the dimensions of perception and evaluation. On the perception dimension,

the "sensing" type is said to perceive objects, in isolation, in terms of their potential value in use, while the "intuition" type is said to perceive objects, in some "global" context, in terms of what the objects might be converted into. On the evaluation dimension, the "thinking" type is said to evaluate objects according to formal systems of reasoning, while the "feeling" type is said to rely on affective processes to make judgments about the "goodness" of objects. Keen (1973; McKenney and Keen, 1974) operationalized these perception and evaluation dimensions via a battery of objective tests. The independence of the postulated dimensions has proved difficult to demonstrate for both the Myers-Briggs Type Indicator and Keen's objective measures.

Single-dimensional classifications have also been developed for cognitive-styles research. Typically, such measures attempt to classify individuals according to whether they contend with information in an analytic (systematic) or a heuristic (intuitive) manner. Examples include Mathes (1969), Huysmans (1970), Mock, Estrin and Vasarhelyi (1972), Barrett, Bevacqua, Rittenberg and Simmermacher (1973), Barkin (1974), Barrett, McKee, Ooi and Brick (1973), and Vasarhelyi (1977). A cognitive-styles instrument developed at the University of Minnesota has been used in several studies (e.g., Barkin, 1974; Benbasat, 1974; Ajinkya, 1976; Black, 1976; Tiessen, 1976), and responses to this instrument have been found to correlate significantly with information selection measures, decision-making time, the presence or absence of "noise" in the information set, and the level of aggregation of information.

Typically, verbal protocols are produced in the following manner. A subject is given very simple and brief "think aloud" instructions before being presented a task to solve. After receiving a problem, the subject is told to think aloud while attempting to formulate a solution. The sounds audibilized by the subject are either audio-taped or audio-video-taped. If the subject ceases to verbalize for more than a few seconds, the researcher "prompts" the subject to renew thinking out loud. When the problem either is solved or the problem-solving session is concluded, the researcher has a transcribed record of whatever was said or transpired.

The researcher must decide how much of a subject's protocol will be analyzed. This determination is governed by the coding strategy employed. It follows that the coding strategy selected will have an important bearing on the type, quality and importance of the results obtained. The objective of a coding strategy is to break up the total protocol in such a way that its structure is not disturbed while at the same time minimizing the verbal content to be coded. Unfortunately, the manner in which a subject's protocol should be broken up into sequences or phrases has neither been adequately stated nor tested. In a recent study the following criterion was employed: "Each phrase was a naive assessment of what constituted a single task assertion or reference by the subject" (Payne, 1976, p. 373; Newell and Simon, 1972, p. 166). What constitutes a phrase, a task assertion, or a reference is not stated. Further, because write-ups of process tracing studies

present only portions of coded protocols, it cannot be determined how coding criteria such as this one are applied; nor can the extent to which such criteria are used consistently (so as not to disturb the structure of that portion of the thought process verbalized) be easily determined.

Questions can be formulated about the reasonableness of the verbal protocol coding strategy employed by a researcher or the consistency with which it is applied, as well as the reliability and the validity of the results and conclusions stated. Such questions should not, however, overshadow the existing and potential fruitfulness of the findings contained in reports of process tracing studies, especially at this juncture when so little is known about human information processing and decision making. Certainly, those conducting process tracing studies appear to be cognizant of the potential limitations of this methodological data collection approach.

Payne et al. (1977) state that research designs employing verbal protocols should, where feasible, incorporate other data collection methods so that the results of multiple methods can be compared to determine their convergence. Additionally, process tracers are generally reluctant to generalize the conclusions derived from the results produced in one task setting to other problem contexts. Employing multimethod research designs and not generalizing from the results of one study to other settings is a healthy state given the relative infancy of process tracing research.

The results of verbal protocol studies have been used to develop predictive computer models of such diverse activities as chess playing (DeGroot, 1965) and security investment portfolio management (Clarkson, 1962). In studies of this gender, these researchers have asked experienced chess players and trust officers to think aloud as they play chess or construct securities portfolios. Computer programs are constructed to model their information processing and choice behavior. These computer models are simulated to produce predictions of decision behavior. Finally, the predictions are compared with actual decisions to determine the degree of convergence, and if necessary, to further adjust the model to improve predictive accuracy.

More recently, Payne (1976), Svenson and Montgomery (1974) and several marketing researchers interested in consumer behavior (P. Wright, 1974a) have used verbal protocols to discover which of several decision rules (Coombs (1964) and Tversky (1972)) were used. Subjects commonly are presented a list of alternatives--e.g., brands of product such as cereal, and a list of attributes or aspects--e.g., size, cost, color of package. They are asked to rate the attractiveness of various attributes and determine which alternative is preferred. Verbal protocols and more conventional methods such as retrospective questionnaire responses are used to collect data. The data is analyzed to determine which of several decision rules apparently was employed to choose the aspects evaluated and which particular alternative finally emerged as the preferred choice.

4. Other Information Processing Research Approaches

The approaches described above are not the only systematic ways of researching human processing of information. An additional approach which has much in common with the Bayesian tradition is signal detection theory. This approach makes an explicit distinction between the person as a sensor and the person as a decision maker. As a sensor, he is concerned with discriminating among different "signals" (produced, for example, by an accounting system) or with discriminating "signal" from "noise." As a decision maker, he is concerned with the use of "signals" in the making of decisions. Optimum decision rules can be developed, given payoffs and prior probabilities over "signals." Introductions to the literature of signal detection theory are found in Coombs, Dawes and Tversky (1970) and Lee (1971).

Another approach to the study of human information processing is integration theory (Anderson, 1968, 1970). This approach may be considered a variant of the regression approach described earlier. It is concerned simultaneously with the problems of scaling and integration of cues. The scaling problem is generally investigated with monotone rescaling procedures, while the integration problem is concerned with testing alternative models about the specific composition rules that decision makers apply to informational cues. Once the model and the response scale are established, subjective scale values for the cues can be derived. Then composition rules are based on these subjective scale values, whereas the regression approach described earlier

three categories, roughly called information set/task variables, decision-maker variables, and judgment/decision variables. The information set/task variables (Table A1) relate to the information component (Y) of Figure 1. The decision-maker variables (Table A2) are reflected in Figure 1 primarily by the "behavioral factors" box and secondarily by the $\hat{X} = o(Y)$ relation. Finally, the judgment/decision variables (Table A3) relate to the human information processing component ($\hat{X}$) of Figure 1.

6. Comparison of the Principal Approaches

The lens, Bayesian and cognitive complexity/cognitive styles approaches to the study of human information processing have received enough research attention that we are able to compare and contrast several important characteristics of these three approaches, and this section is devoted to such comparisons. The process tracing approach, having no research tradition in accounting at this point in time, is omitted in these comparisons.

The dimensions along which we compare the lens, Bayesian and cognitive complexity/cognitive styles approaches include (1) the inputs required for the approaches, (2) the outputs extracted from the approaches, (3) measures of data diagnosticity and related subjective composition rules, and (4) optimality criteria.

As noted in Section 3.2, within the regression or discriminant analysis operationalization of the lens model, the cues may take on

continuous sets of values, and the cue-criterion relationships, as well as cue intercorrelations, may reflect environmental data relationships. When the lens model is operationalized via analysis-of-variance, however, discrete or categorical values are generally used, especially if the researcher wishes to include a full (or a substantial fractional) replication of cue value combinations. Discrete or categorical values are typically used in the Bayesian approach also. However, as observed in Section 3.1, continuously varying data and a continuous set of hypotheses can be handled in the Bayesian approach. Another distinction between lens and Bayesian research is that data are typically presented simultaneously in the former approach but in a sequential mode in the latter approach. In contrast, the cognitive complexity/cognitive styles approach places fewer restrictions on the researcher in terms of input; for example, both simultaneous and sequential presentations of both categorical and continuously varying data can be accommodated. Further, certain behavioral qualities of the data (eucity, noxity) can also be included for investigation.

In terms of output, other differences exist among the approaches. In lens model studies, subjects generally provide (single) judgments on the basis of less than five x_k for each y_n. The number of judgments obtained is determined by stability conditions required for the linear multiple regression models which describe each side of the lens and the context of the study. In terms of the cognitive effort required from subjects, fairly complex conditional (central tendency) point estimates must be generated.

As noted in Section 3.1, Bayesian experiments require relative likelihood assessments (perhaps in the form of odds) for two or more states of each y_n variable. In many of the early Bayesian studies the "bookbag and poker chip" situation was employed where a two-state distribution (y_j; j=1,2) is revised multiple times given drawings from one of the bookbags. Notice that only one y_n and repeated realizations of only one x_k were needed to study subject assessments relative to Bayes' Rule. More complex (and externally valid) situations would require J to be greater than two and probably N greater than 1; however, note that such a study would require (J × N × time periods) data points from subjects, where a similar lens model study would require only (N × time periods) assessments.

In summary, while the typical output of a lens model study is a point estimate, the typical output of a Bayesian study is a probability distribution. In both the lens and Bayesian approaches, however, the decision maker typically occupies a very passive role (Einhorn, 1976). In the cognitive complexity/cognitive styles approach, the decision maker must be more active. He generally must integrate several data from a diversity of sources into a "large-scale" decision--for example, the amount to buy, sell, produce, spend on advertising, etc., in business gaming contexts, or even larger-scale decisions in other contexts such as tactical war games or international simulations.

These three approaches to studying human information processing may also be compared by examining measures of data diagnosticity

and related subjective composition rules. It is perhaps in this respect that the lens and Bayesian approaches differ most substantially from the cognitive complexity/cognitive styles approach. The latter approach offers no measure of the diagnostic impact of data, nor does it offer a clear way of hypothesizing subjective composition rules. The Bayesian approach offers the likelihood measure, $P_i(x_k|y_j)$, as an indication of the relevance that a particular x_k has for changing $P_i(y_j)$ to $P_i(y_j|x_k)$ for event j. Alternatively, likelihood ratios may be used as measures of data diagnosticity (see Equation 4). Since the measure of diagnosticity in the Bayesian approach is in the form of likelihoods or likelihood ratios, it is natural that subjective composition rules are conceptualized and investigated in terms of $P_i(x_k|y_j)$ probabilities or in terms of subjective likelihood ratios. In the lens model approach, various correlation and regression statistics have been suggested as measures of diagnosticity, including r_{ek}, $\hat{\beta}_{ek}$, and part (semipartial) correlations. Similar measures have been suggested for the subject side of the model, along with other measures--e.g., $RW = (r_{ek}\hat{\beta}_{ek})/R_s^2$ (Hoffman, 1960). In the absence of cue intercorrelation, the suggested measures give equivalent indications of the relative diagnostic impact of each cue. For the more typical case of nonzero intercorrelation, the part correlation appears preferable (Darlington, 1968; Wright, 1977c). In the analysis-of-variance variant of the lens model approach, ω^2 (Hays, 1973) is often used as a measure of the diagnostic impact of each cue.

Concerning optimality criteria, both the lens and Bayesian models provide performance standards for analysis of subject judgments; however, the orientation of the two models is somewhat different. In the lens model, the emphasis is on comparison of how individuals utilize data (indicated by $\underline{y}_i$, $\hat{\underline{y}}_i$, r_{ik} and R^i_s) relative to environmental data relationships ($\underline{y}_e$, $\hat{\underline{y}}_e$, r_{ek} and R_e), with emphasis on judgmental accuracy and linear description of information processing. Bayesian studies typically concentrate on generation and comparison of subject judgment distributions relative to the internal consistency conditions required by probability theory. If environmental relative frequencies for information variables are available (i.e., "objective" $\phi(x_k|y_j)$ indications) or a statistical model seems to be representative of the process generating the x_k, comparison of subject judgment distributions with environmental conditions may be performed.

Reliance upon correlation and regression statistics in the lens model approach implies the acceptance of a built-in payoff function: the least-squares criterion of goodness of fit (Slovic and Lichtenstein, 1971). On the other hand, the posterior probabilities of the Bayesian approach may be combined with <u>any</u> payoff function (quadratic, linear, logarithmic, etc.) to determine the best action, and the Bayesian approach is often incorporated in normative decision theory with its emphasis on maximization of expected utility (or expected value, as a special case).

As noted earlier, a Bayesian measure of data diagnosticity is the likelihood ratio (BLR), and subjective composition rules are

TABLE 1

CHARACTERISTICS OF THREE APPROACHES TO HUMAN INFORMATION PROCESSING RESEARCH

Dimension	Lens	Bayesian	Cognitive Complexity Cognitive Style
Input	correlation or discriminant analysis approach: continuous data; anova approach: categorical, artificial data	typically categorical data, although continuous can be handled	wide-ranging data types; focus on load, eucity, [illegible]
Data diagnosticity	$\hat{\beta}_{ek}$; r_{ek}; part r; ω^2	$P_i(x_k \mid y_j)$; likelihood ratio	no measure of data diagnosticity
Subjective composition rules	$\hat{\beta}_{ik}$; r_{ik}; part r; ω^2; RW	subjective likelihood ratio or subjective log likelihood ratio	no measure of subjective composition rules
Output	fractile of probability distribution	probability distribution	"macro" decisions--e.g. amount to produce, spend, etc.
Criterion	goodness-of-fit criterion (typically least squares)	posterior probabilities can be combined with any payoff function to determine best decision	no established link between "level of information processing" and quality of decisions, or between cognitive styles and quality of decisions
Comparison with optimal model	linear model estimates	Bayesian revision	no optimal model
Dependent variables for analysis	r_a^i; r_o^i; r_m^i; $\hat{\beta}_{ki}$; RW_{si}; r_e^i; ω^2	estimates of $P_i(x_k \mid y_j)$ or $P_i(y_j \mid x_k)$; SLR; SLLR; SLLR + BLLR	processing variables--amount of information used or purchased; decision time, etc. performance variables--time, costs, profit--in particular experimental setting

task-related activity required of subjects (e.g., whether information selection, as well as information utilization, is required). However, more than one approach is generally appropriate for researching a particular issue, and we try especially to recognize the relevance of alternative approaches in the discussion that follows.

First, it should be noted that the approaches have some commonalities. This is especially true of the lens and Bayesian approaches. All the approaches are concerned with information-integration activities and with how man attempts to interpret and predict his environment (Libby and Lewis (forthcoming); Snowball, 1976). Each approach searches for patterns (across individuals) in judgmental processes. On the other hand, each approach has distinctive characteristics (e.g., the focus on judgmental accuracy and reliability versus the postulation of psychological constructs) which make it more or less appropriate for researching a given human information processing issue.

The tasks which are typically studied via the Bayesian and lens model approaches are very structured (Einhorn, 1976). In contrast, the cognitive complexity/cognitive styles and process tracing approaches allow the researcher to investigate less structured, nonrecurring, more complex task settings. Of course, this increased complexity (and realism) is not without cost. In the cognitive complexity/cognitive styles approach, a trade-off exists between the capturing of more realistic tasks and the ability to compare the resulting judgments with optimality criteria or to otherwise assess the quality of judgments.

If one's research requires a measure of optimality, or relative accuracy, application of either the Bayesian or lens model approach is needed. Further, if a measure of data diagnosticity is necessary, the lens model or Bayesian approach is required. Such a need is most apparent when the central concern is implied cue usage, or weighting, rather than simply prediction. Description of judgments has been one key focus of accounting-related research to date (e.g., Ashton, 1974a, b; Joyce, 1976; Wright, 1977b). In addition, the process tracing approach may profitably be employed when the concern is description of the processes used to generate judgments.

Einhorn (1976) further notes that the typical Bayesian or lens model study provides the subject with perfectly reliable cues, that information search is not required, and that the range of hypotheses for data use which can be generated by the subject is restricted because a particular dependent variable is specified for him.

Obviously, the cognitive complexity/cognitive styles and process tracing approaches allow the inclusion of data of imperfect reliability; however, recent developments in the Bayesian approach make it amenable to unreliable data also. The optimal model in such cases is a modified Bayes theorem (Gettys and Willke, 1969), and this model has served as a criterion for several studies. (See, for example, the entire December 1973 issue of Organizational Behavior and Human Performance.) Some work with unreliable cues has been suggested within the lens model approach also (e.g., Brehmer, 1970).

In terms of the information search, or information-seeking, behavior of decision makers, the cognitive complexity/cognitive styles and process tracing approaches may profitably be employed. The complexity of the task settings presented to decision makers in the cognitive complexity/cognitive styles approach (e.g., Barrett et al., 1976; Driver and Mock, 1975; Mock and Vasarhelyi, 1976) lends itself to information-seeking behavior. Moreover, the disadvantage of having no clear measures of optimality and data diagnosticity, which is characteristic of the cognitive complexity/cognitive styles approach, is less important in information-seeking research than in information-utilization research. Thus, one area in which the cognitive complexity/cognitive styles approach may have a relative advantage is that of information seeking. It should be noted, however, that information seeking has been studied fairly extensively within the Bayesian approach. The focus is generally upon the ability of individuals to determine the optimum point at which to stop gathering additional information, or sampling, given certain probabilities, benefits, and costs of information. The decision maker's performance may be compared to that of an optimal stopping model (e.g., Edwards, 1965). In contrast to the cognitive complexity/cognitive styles and Bayesian approaches, the lens model approach is relatively ill-suited for information-seeking research.

Some of the conclusions resulting from protocol analysis research may have important implications for those interested in studying

information search. Payne (1976), for example, states that his findings suggest that information search patterns are likely to vary with the level of task complexity encountered. In a two-alternative choice situation he found that decision makers searched the same amount of information for each alternative (evaluated the same number of aspects), whereas when faced with either six or twelve alternatives these same subjects searched a variable amount of information across the various alternatives. He concludes that the constant information search behavior in the two-alternative choice setting is compatible with a compensatory decision rule, whereas variable information search behavior is consistent with either the conjunctive or elimination-by-aspects decision rule. These findings suggest, among other things, that the linear additivity by attractiveness assumption of classical utility theory, which is a fundamental tenet of the Bayesian probability revision model, may hold for only a two-alternative information-search setting. Payne also reports that not only is task complexity (the number of alternatives presented and the number of aspects which can be evaluated) an important determinant of the decision rule employed, but individual differences also were evident in his study. He found that a few subjects switched from one decision rule to another as they searched information in order to solve more complex problems.[16]

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[16]Currently, there is at least one study underway that uses verbal protocols to uncover which of several decision rules are used to search accounting information in order to solve an earning power assessment problem. Stanley Biggs, a doctoral student at the University

but only in a limited sense. Slovic and Lichtenstein (1971) lamented the strong tendency of human information processing researchers in psychology to be unaware of the existence of comparable research under both the Bayesian and regression paradigms. They suggested that a multiparadigm approach be used, "searching for the most appropriate tasks and models to attack the substantive problems of interest" (p. 726). Such advice seems equally appropriate in accounting-related human information processing studies.

A P P E N D I X

This appendix presents a classification of several variables of interest to human information processing researchers in both psychology and accounting. It is adapted from a similar classification by Libby and Lewis (forthcoming), and it includes some material from Slovic and Lichtenstein (1971) and Snowball (1976). Such a classification can serve as a method of organizing a large and rapidly growing body of literature and as a tool in future research through which accounting issues can be abstracted to underlying generic information-processing issues. More specifically, it should help alleviate the current situation in which such variables are typically considered only post hoc in attempts to explain differing research results among studies. If researchers are aware, ex ante, of the many combinations of variables which have been (and can be) included in a human information processing study, they may be able to design experiments more sensibly and to formulate hypotheses more definitively than they could without such a classification. Moreover, this type of classification may assist researchers in the assessment of the generalizability of their results to other settings, and to relate accounting research findings to both psychological research findings and to other accounting research.

It should be emphasized that all the variables listed in Tables A1, A2, and A3 are not necessarily equally important for any particular human information processing study or for any of the research

approaches discussed. Nor is it necessarily true that all these variables have been investigated; many of them have not, particularly in accounting contexts. Furthermore, any study will likely include a number of these variables and will potentially add to our knowledge in serveral categories.

TABLE A1

VARIABLES OF INTEREST - INFORMATION SET AND TASK

I. Information Set

- A. Scaling Characteristics of Individual Cues
  - 1. Level of Measurement (e.g., Nominal, Ordinal)
  - 2. Objectivity of Measurement
  - 3. Discrete or Continuous
  - 4. Deterministic or Probabilistic
- B. Statistical Properties of the Information Set
  - 1. Number of Cues
  - 2. Distributional Characteristics (e.g., Variability, Extremity)
  - 3. Cue-Criterion Relationships
    - a. Cue Validity
    - b. Positive or Negative Relationship
    - c. Linear or Nonlinear Relationship
  - 4. Interrelationships of Cues
    - a. Cue Consistency
    - b. Cue Redundancy
  - 5. Underlying Dimensionality of Cues
    - a. Cue-Response Compatibility
    - b. Cue-Cue Compatibility
- C. Cue Content
  - 1. Predictive Significance
    - a. Diagnosticity
    - b. Diagnostic Direction
    - c. Bias (Systematic Error)
    - d. Reliability (Random Error)
  - 2. Behavioral Factors
    - a. Noxity
    - b. Eucity
    - c. Source Credibility
- D. Method of Presentation
  - 1. Format (e.g., Numerical, Graphical, Verbal)
  - 2. Order
    - a. Sequential
    - b. Simultaneous
  - 3. Level of Aggregation

II. Task

- A. Type of Task
  - 1. Degree of Complexity
  - 2. Structured or Unstructured
  - 3. Recurring or Nonrecurring
  - 4. Personal or Organizational
  - 5. Range of Hypotheses Permitted
  - 6. Active or Passive Role of Decision Maker
- B. Characteristics of Task
  - 1. Task Predictability
  - 2. Prior Probabilities
  - 3. Data Generator
  - 4. Response Mode
  - 5. Social Influences
  - 6. Uniformity of Information Over Cases
- C. Task Training

III. Experimental Context

- A. Obtrusiveness
- B. Physical Viewing Conditions
- C. Objective
- D. Costs and Rewards
- E. Information about Cue Attributes
- F. Feedback

TABLE A2

VARIABLES OF INTEREST - THE DECISION MAKER

I. Characteristics of Decision Maker

- A. Human or Mechanical
- B. Number of Decision Makers
- C. Personal Characteristics
  - 1. Intellectual Ability
  - 2. Personality
  - 3. Cognitive Structure
    - a. Cognitive Complexity
    - b. Cognitive Style
      - · primary mode of data perception
      - · primary mode of data evaluation
  - 4. Attitudes
  - 5. Demographics (e.g., Age, Sex, Occupation, Education)
  - 6. Cultural Background
- D. Task-related Characteristics
  - 1. Prior Experience
    - a. In General
    - b. In Particular Task
  - 2. Interest and Involvement

II. Characteristics of Decision Rule

- A. Form
  - 1. Linear or Nonlinear
  - 2. Compensatory or Noncompensatory
- B. Cue Usage (Weighting)
- C. Stability
- D. Heuristics

III. Influences on Ability to Learn

- A. Positive or Negative Relationships
- B. Linear or Nonlinear Relationships
- C. Number of Cues
- D. Type of Feedback
- E. Functional Fixation
- F. Use of Decision Aids

IV. Information-Seeking Behavior

- A. Amount of Information
- B. Type of Information
- C. Optimal Stopping

TABLE A3

VARIABLES OF INTEREST--THE JUDGMENT OR DECISION

I. Qualities of the Judgment or Decision

- A. Accuracy (Validity)
- B. Speed (Decision Time)
- C. Reliability
  1. Consistency (Stability)
  2. Consensus
  3. Convergence
- D. Response Biases
- E. Predictability

II. Self-Insight

- A. Subjective Cue Usage
- B. Perceived Decision Quality
- C. Perceived Characteristics of Information Set and Task

III. Amount of Information Used (or Purchased)

- A. Relevant Information
- B. Irrelevant Information

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