Decision Making in Information-Rich Environments: The Role of Information Structure

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Today's consumers are often overloaded with information. This article argues that traditional approaches to measuring the amount of information in a choice set fail to account for important structural dimensions of information and may therefore incorrectly predict information overload. Two experiments show that a structural approach to measuring information, such as information theory, is better able to predict information overload and that information structure also has important implications for information acquisition. A Monte-Carlo simulation, in which decision rules are applied to multiple information environments, shows that the amount of information processing mediates the relationship between information structure and information overload.

Today's consumers face richer information environments than ever before. Whether it is the 13,798 mutual funds on Quicken's Web site or the 1,057 PDAs on Amazon's Web site, it is clear that today's consumers have many choices. Several researchers (e.g., Jacoby, Speller, and Kohn 1974a, 1974b; Keller and Staelin 1987; Malhotra 1982; Scammon 1977) have found evidence that increasing the number of alternatives or attributes in a choice set leads to a decline in the quality of consumers' choices. (See Keller and Staelin [1987] for a review.) Other research has shown that consumers are less likely to purchase a product when a store offers an extensive selection of that product than when the selection is reduced (Iyengar and Lepper 2000). What factors affect the amount of information that consumers are asked to process and the likelihood that they will be overloaded with information?

This article argues that the amount of information in a choice set, and therefore the likelihood of information overload, depends on multiple structural factors of information. Failing to account for these factors may lead to a faulty prediction of overload. Information structure has important implications for information acquisition, the amount of information processing, and decision quality. As such, this article provides an important conceptual link between research on information overload (Jacoby et al. 1974a, 1974b; Keller and Staelin 1987; Malhotra 1982) and research on decision processes (Bettman, Johnson, and Payne 1990; Creyer, Bettman, and Payne 1990; Johnson and Payne 1985; Payne, Bettman, and Johnson 1988). Two experiments and a Monte-Carlo simulation examine how information structure affects information acquisition, decision processes, and decision quality.

MEASURING INFORMATION

Traditional approaches to measuring the amount of information provided to consumers (e.g., Bettman et al. 1990; Jacoby et al. 1974a, 1974b; Keller and Staelin 1987; Malhotra 1982; Payne 1976; Payne et al. 1988; Wright 1975) involve simple counts of the number of alternatives and attributes in a choice set. These counts are then used to make predictions about decision processes and the quality of consumers' choices. Such an approach assumes that more alternatives mean more information. However, is it possible to provide consumers with more alternatives but less information?

Formal measures of information structure (information theory) developed by Shannon (1949) and extended by Garner (1962) offer a potential alternative to traditional approaches. Information theory proposes that the amount of

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information is a measure of the number and probability of outcomes; more formally,

$$I(A) = -\sum_{i=1}^{m} p(a_i)\log_2 p(a_i), \quad \textbf{(1)}$$

where a_i (a_1, a_2, . . . a_m) are discrete outcomes. In the domain of consumer choice, a_i (a_1, a_2, . . . a_m) may be thought of as the attribute levels of attribute A, and $p(a_i)$ is the relative frequency of a_i among alternatives. Unlike context variables, such as interattribute correlation and decision rules, information structure is a task variable that can be measured independently from particular data values (Bettman, Johnson, and Payne 1993). Information structure interacts with context variables to affect the amount of effort involved in making a decision, information acquisition, and decision strategies, as well as decision quality.

A structural approach to information suggests that there are multiple dimensions determining the amount of information (potential outcomes) that consumers need to process when making choices among a given set of product alternatives. These include the number of alternatives, the number of attributes, the number of different attribute levels associated with each attribute, and the distribution of attribute levels across alternatives. As a measure of the amount of information in a choice set, information structure should provide an indication of the amount of information processing necessary to make a decision.

Formal measures of information have been used extensively in psychology and economics (for reviews see Garner [1962] and Dawes [1970]). In marketing, structural (i.e., information theoretic) measures have been used to predict brand switching (Herniter 1973), estimate consideration sets (Gensch and Soofi 1995), measure consumer variety seeking (Kahn 1995) and preferences (Glazer 1984), and manipulate the informativeness of feedback (West 1996).

Because the structural approach encompasses the simple counts of previous research, it can be used to account for previous research showing that an increase in the number of alternatives (attributes) can lead to declines in decision quality. When attribute levels are evenly distributed across alternatives, as in previous research (Bettman et al. 1993; Jacoby et al. 1974a, 1974b; Keller and Staelin 1987; Malhotra 1982; Payne et al. 1988), equation (1) reduces to

$$I(A) = \log_2 a, \quad \textbf{(2)}$$

where a is the number of attribute levels of attribute A.

INFORMATION STRUCTURE AND INFORMATION OVERLOAD

A structural approach suggests that the amount of information to process increases with the number of attribute levels and is greatest when attribute levels occur with uniform probability. This means that the likelihood of information overload should be higher and choice quality lower when attribute levels are uniformly distributed across alternatives or when there are more attribute levels. For example, if 50% of calculators offered by a consumer electronics Web site have one-line screen displays and 50% have two-line displays, there is more uncertainty and, therefore, more information to gain by examining the calculators, than if 90% of calculators have one-line displays and 10% have two-line displays. In addition, a structural approach suggests that although an increase in the number of alternatives in a choice set may lead to overload when all other factors are held constant, the same increase in the number of alternatives may not lead to overload when factors such as the distribution of attribute levels across alternatives and the number of attribute levels are also changed. For example, a choice set with more alternatives can have fewer attribute levels (e.g., two instead of four types of screen displays), or the attribute levels in the larger set can be nonuniformly distributed across alternatives. This implies that the impact of the number of alternatives on choice quality will be mediated by information structure.

From the general proposition that information overload is a function of the amount of information $I(A)$ in a choice set, come the following testable hypotheses:

H1a: The even (uniform) distribution of attribute levels across alternatives lowers decision quality relative to the uneven (nonuniform) distribution of attribute levels;

H1b: An increase in the number of attribute levels lowers decision quality.

H2: Information structure mediates the relationship between the number of alternatives and decision quality.

Hypothesis 1 suggests that choice sets with attribute levels distributed evenly across alternatives, or those with more attribute levels, are more likely to be associated with information overload than those for which attribute levels are not evenly distributed across alternatives. Hypothesis 2 suggests that information structure, not just the number of alternatives or attributes, is the primary determinant of information overload. In particular, a choice set with more alternatives but unevenly distributed attribute levels may in fact lead to decision outcomes that are not significantly worse than a set with fewer alternatives with an even distribution of attribute levels across alternatives.

INFORMATION STRUCTURE AND INFORMATION PROCESSING

As a measure of the total amount of information in a choice set, information structure is also a measure of the average amount of information associated with a particular element. Because decision makers often adapt their decision-making processes to the decision environment (Payne et al.

1988), information structure may have important implications for information processing as well as decision quality.

Process tracing methods such as Mouselab (Payne et al. 1988), eye tracking (Russo and Dosher 1983), or verbal protocols (Jarvenpaa 1989) may be used to assess information acquisition. Although not a measure of the use of a particular decision rule (Bettman et al. 1993), information acquisition can be used as a proxy for the amount of information processing, the amount of processing effort, and selectivity in processing (Creyer et al. 1990; Jarvenpaa 1989; Payne 1976; Payne et al. 1988). In particular, the amount of information processing can be assessed by counting the number of times that information boxes are opened (acquisitions) for a particular decision; the amount of processing effort can be measured as the time spent per acquisition; and processing selectivity can be determined by the proportion of time spent on the most important attribute, the variance in time spent on each alternative, and the variance in time spent on each attribute (Creyer et al. 1990; Payne et al. 1988).

Amount of Information Processing

A structural approach to measuring information suggests that the even distribution of attribute levels raises the amount of information associated with each information element by increasing the decision maker's uncertainty that a particular alternative takes on a particular attribute value. In other words, the even distribution of attribute levels makes it harder for the decision maker to guess the attribute value for a given alternative; acquiring information about that attribute provides more information. This should slow down the rate at which information is processed.

Similarly, an increase in the number of attribute levels raises the amount of information associated with each attribute by raising a decision maker's uncertainty about possible attribute values. In other words, more attribute levels also make it harder for the decision maker to guess the attribute value; acquiring information about an attribute with four levels provides more information than acquiring information about an attribute with two levels. Because the even distribution of attribute levels or an increase in the number of attribute levels raise the average amount of information associated with each attribute by alternative combination, decision makers should take more time to acquire and process information. Under time pressure, this should decrease the total number of acquisitions per decision.

H3: When time pressure is high, the even distribution of attribute levels across alternatives:

(a) increases the average amount of time per acquisition;
(b) decreases the number of acquisitions.

H4: When time pressure is high, an increase in the number of attribute levels:

(a) increases the average amount of time per acquisition;
(b) decreases the number of acquisitions.

In other words, an increase in the amount of attribute information, whether through the distribution of attribute levels or the number of attribute levels, is expected to lead to a higher average time per acquisition and fewer acquisitions under time pressure. Note that these hypotheses question the assumption that information acquisition takes the same amount of time regardless of information structure (e.g., Bettman et al. 1990).

Processing Selectivity

Previous research has shown that decision makers often adapt their decision strategies to the information environment (Payne, Bettman, and Johnson 1993) and that choice sets with more alternatives are associated with less compensatory processing (Payne 1976). This suggests more generally that choice sets that contain more information should be associated with less compensatory processing, even if there is no increase in the number of alternatives and attributes. Noncompensatory decision rules are associated with higher variance (greater selectivity) in processing across alternatives and attributes, while compensatory decision rules involve more uniform processing of information of alternative and attribute information (Bettman et al. 1993; Payne et al. 1988). In particular, noncompensatory decision processes lead to an increase in time spent on information related to the most important attribute and to greater variance in time spent per attribute and time spent per alternative (Creyer et al. 1990). Since choice sets with attribute levels distributed evenly across alternatives and those with more attribute levels contain more information, they should be associated with greater selectivity in processing.

H5a: Under time pressure, the even (uniform) distribution of attribute levels across alternatives increases processing selectivity;

H5b: Under time pressure, an increase in the number of attribute levels increases processing selectivity.

Hypothesis 1 proposes that the even distribution of attribute levels or an increase in the number of attribute levels will lead to declines in decision quality. Hypothesis 2 proposes that information structure mediates the effect of an increase in the number of alternatives on decision quality. In particular, choice sets with more alternatives but for which attribute levels are unevenly distributed may not be associated with declines in decision quality. Hypotheses 3 and 4 propose that the even distribution of attribute levels or an increase in the number of attribute levels will increase the amount of time spent on each acquisition and lower the number of acquisitions made under time pressure. Hypothesis 5 proposes that the even distribution of attribute levels or an increase in the number of attribute levels will lead to greater selectivity (higher variance) in processing under time pressure.

Two experimental studies examine these hypotheses. Hypotheses 1a and 2 are tested in an experiment that examines the relationship between information structure and information overload. Hypotheses 1b, 3, 4, and 5 are tested in a second experiment that extends study 1 by examining how information structure affects information processing as well as decision quality.

STUDY 1

Method

Participants and Procedure. Participants (143 undergraduate students) were asked to imagine they had decided to buy a calculator from Electronics USA, an online retailer of consumer electronics that carries several models of pocket calculators and provides ratings on calculator attributes. They were also told that each of the available calculators costs the same amount ($29.95), a price within their budget. (See Biehal and Chakravarti [1983] for a similar task.)

Participants were told that a recent *Consumer Reports* article suggests that there are several dimensions to consider when buying a calculator. These include versatility (rated from one to 10 stars with 10 as the best), ease of use (rated from one to seven stars with seven as the best), battery life (ranging from three to 15 hours), warranty (ranging from three months to five years), weight (ranging from one-half to 12 oz.), memory size (ranging from four to 264 kb) and screen size (ranging from one to eight lines). To help participants in their decision, a friend had indicated the importance weights of each of the seven attributes on a 100-point scale (high versatility = 70, high ease of use = 60, long battery life = 50, long warranty = 40, low weight = 40, large memory = 30, and large screen = 30). In addition, there was a best (or dominant) calculator that was equal to or better than all other alternatives on every attribute. The importance weights and dominant alternative provide a normative sense of choice "goodness" and avoid potential measurement errors associated with using participants' own preferences to determine the best choice (Meyer and Johnson 1989; Payne et al. 1993). Four lottery prizes of $25 were offered as incentives for participants to make the "best" choice. In order to prevent ceiling effects and ensure that there would be "information overload," participants were given only two minutes to make their choices. Those who did not make a choice within that time would be ineligible for the lottery.

Information was presented in a matrix form simultaneously for all alternatives. A randomly generated single letter and three-digit number identified each calculator model. At the bottom of the screen participants could mark, out of the 18 or 27 available, the calculators they would consider buying for their friend and write the name of the calculator they wished to purchase. This was used to determine the probability that the dominant calculator was considered, the probability that the dominant calculator was chosen, and choice quality relative to the best and worst alternatives in the choice set.

Experimental Variable

Information Structure. Information structure was manipulated at four levels using a 2 (18 or 27 alternatives) × 2 (even or uneven distribution of attribute levels across alternatives) between-participants design. This design allows the replication of previous results, that increasing the number of alternatives lowers the probability of choosing the "best" alternative and creates conditions in which increasing the number of alternatives may not lead to declines in decision quality.

The distribution of attribute levels across alternatives was manipulated by changing the distribution of attribute levels of four of the seven attributes (warranty length, weight, memory, and screen size), each of which occurred at three levels. In the "even" conditions, the three levels of each of the four manipulated attributes were evenly distributed across 18 or 27 alternatives; in the "uneven" conditions, seven-ninths of the calculators had one level, one-ninth of the calculators had the second level, and one-ninth of the alternatives had the third level for each of the four attributes. In the uneven distribution of attribute levels condition, in order to avoid confounding the manipulation of the distribution of attribute levels with the skew of attribute levels, the distribution of attribute levels was chosen so that the dominant calculator shared the same level as the majority of calculators for two of the attributes, warranty and memory, and was in the minority of calculators for two of the attributes, weight and screen size. The three levels of the nonmanipulated attributes (versatility, ease of use, and battery life) were evenly distributed across alternatives, and the values of these attributes were identical in all conditions. In study 1, average interattribute correlations were around zero in both even (high information) and uneven (low information) distribution conditions (r's = .002 and .003, NS). This controls for the potential effects of interattribute correlation in which choice sets with positively correlated attributes are associated with higher choice quality than those with negatively correlated attributes (Bettman et al. 1993). The order of alternatives was determined randomly but was the same for all participants. To allow choice quality to be compared, the attribute values of the dominant alternative were the same in all four conditions.

Each choice set had either 18 or 27 calculators. Together, the manipulations of attribute levels and the number of calculators provided participants in the 18-alternative-uneven distribution condition with 36.28 bits of information, participants in the 18-alternative-even distribution condition with 46.26 bits of information, participants in the 27-alternative-uneven distribution condition with 41.37 bits of information, and participants in the 27-alternative-even distribution condition with 52.75 bits of information. This suggests that overload is more likely to be observed when comparing the 36.28-

TABLE 1

STUDY 1: CHOICE, CONSIDERATION, AND CHOICE QUALITY

	Uneven distribution		Even distribution	
	18 alternatives (36.28 bits)	27 alternatives (41.37 bits)	18 alternatives (46.26 bits)	27 alternatives (52.75 bits)
Choice (corrected)[a]	.68 (21/30)	.56 (18/31)	.58 (17/28)	.35 (10/27)
Consideration (corrected)	.79 (24/30)	.70 (22/31)	.55 (16/28)	.50 (14/27)
Choice quality	.96 (.04)	.95 (.04)	.78 (.05)	.65 (.05)

NOTE.—The number of bits (amount of information) in each condition is determined by the number of alternatives and the distribution of attribute levels. Choice and consideration are the chance-corrected proportion of participants that chose or considered the dominant alternative in each condition. Actual frequencies are shown in parentheses. Choice quality is the multiattribute utility of the chosen alternative relative to the best and worst alternatives in the choice set. Standard deviations are in parentheses.

[a]Choice and consideration proportions are corrected for chance following Malhotra (1982): $\overline{P}_i = (P_i - P_{ic})/(1 - P_{ic})$, where $\overline{P}_i$ = the proportion of correct choice adjusted for chance, $\overline{P}_{ic}$ proportion of correct choice by chance alone, and $\overline{P}_i$ = the observed proportion of correct choice unadjusted for chance factors.

bit and 52.75-bit conditions and less likely to be observed when comparing the 46.26-bit and 41.37-bit conditions—even though each involves an equal increase in the number of alternatives from 18 to 27 and provide information on the same seven attributes.

Dependent Measures

Probability of Choice and Consideration. Participants were asked to mark the calculators they would consider buying for a friend and to write down the name of the calculator they wanted to buy for their friend. To allow the 18 and 27 alternative conditions to be compared, the probabilities of choice and consideration were corrected for chance factors (Malhotra 1982; Malhotra, Jain, and Lagakos 1982).

Choice Quality. Choice quality was assessed in terms of the relative weighted additive utility of each choice (Creyer et al. 1990; Johnson and Payne 1985; Payne et al. 1988):

$$\text{Choice Quality} = \frac{\text{Weighted Additive Value}_{\text{Choice}} - \text{Weighted Additive Value}_{\text{Worst}}}{\text{Weighted Additive Value}_{\text{Best}} - \text{Weighted Additive Value}_{\text{Worst}}}. \quad \textbf{(3)}$$

This measure is bounded by one if the best choice is selected and zero if the worst choice is selected.

Results

One hundred and sixteen participants (81%) finished within the two-minute period. Those who did not finish within the allotted time were dropped from the analysis.

Experimental Checks. The distribution of attribute levels manipulation was measured with two seven-point Likert scales: “Many of the calculators were the same weight” and “Many of the calculators had the same size memory.” Since the correlation of these measures was not high ($r = .45$), separate analyses were conducted for each measure. The 2 × 2 ANOVA results show that participants in the uneven distribution condition perceived attributes to be more similar in weight (M’s = 4.98 and 4.31; $F(1, 112) = 6.84, p < .01$) and more similar in memory size (M’s = 4.89 and 4.29; $F(1, 112) = 5.84, p < .05$) than participants in the even distribution condition. The manipulation of the number of alternatives was tested using one seven-point Likert scale: “There were many calculators to choose from.” The 2 × 2 ANOVA results show that participants in the 27-calculator condition perceived there to be more alternatives in the choice set than participants in the 18-calculator condition (M’s = 6.50 and 6.12; $F(1, 112) = 4.26, p < .05$).

Effect on Choice, Consideration, and Choice Quality. Table 1 shows chance-corrected choice and consideration proportions as well as choice quality scores in the four conditions. Logistic regression shows that increasing amounts of information significantly lowered the chance-corrected probability of choosing ($B = -.34$, SD = .16; Wald $\chi^2(1, N = 116) = 4.65$, $p < .05$) and considering the best alternative ($B = -.47$, SD = .17; Wald $\chi^2(1, N = 116) = 7.87, p < .01$). ANOVA results show that increasing amounts of information lowered choice quality (M’s = .96, .95, .78, and .65) in the 36.28, 41.37, 46.26, and 52.75 bit conditions, respectively ($F(3, 112) = 10.95$, $p < .0001$). Polynomial contrasts revealed a significant linear trend of information structure on choice quality ($F(1, 112) = 32.03$, $p < .0001$). Higher order trends were not significant.

The analysis supports hypothesis 1a, that the even distribution of attribute levels lowers decision quality. When attribute levels were evenly distributed across alternatives, the dominant calculator was less likely to be chosen (adjusted proportions = 0.47 and 0.62, $z = 1.67, p < .05$) and less likely to be considered (adjusted proportions = 0.52 and 0.74, $z = 2.45$, $p < .01$) than when attribute levels were unevenly distributed. The ANOVA results for the choice quality scores show that the even distribution of attribute levels was associated with lower quality choices than the uneven distribution of attribute levels (M’s = .72 and .96; $F(1, 112) = 29.19$, $p < .0001$, $\eta_p^2 = .21$). The interaction between the number of alternatives and the distribution of attribute levels was not significant ($F(1, 112) = 1.61$, NS).

Results also support hypothesis 2, that information structure mediates the relationship between the number of alternatives and choice quality. As mentioned above, an increase in the amount of information in the choice set significantly lowered the probability of choosing and considering the best alternative. An increase in the number of alternatives lowered the probability of choosing ($B = -.07$, SD $= .04$; Wald $\chi^2(1, N = 116) = 2.79$, $p < .05$ [one-tailed]) and directionally lowered the probability of considering ($B = -.07$, SD $= .04$; Wald $\chi^2(1, N = 116) = 2.79$, $p < .05$ [one-tailed]) the best alternative. An increase in the number of alternatives in the choice set also marginally lowered average choice quality (M's $= .80$ and $.87$; $F(1, 116) = 2.57$, $p < .06$ [one-tailed], $\eta_p^2 = .02$). When both the amount of information and number of alternatives are used to predict the probability that the best alternative is chosen, the number of alternatives is no longer significant ($B = .49$, SD $= .39$; Wald $\chi^2(1, N = 116) = 1.57$, NS [one-tailed]), but the amount of information remains significant ($B = -.30$, SD $= .16$; Wald $\chi^2(1, N = 116) = 3.46$, $p < .05$ [one-tailed]). For the probability that the best alternative is considered, the number of alternatives is not significant ($B = -.01$, SD $= .05$; Wald $\chi^2(1, N = 116) = .03$, NS [one-tailed]), but the amount of information remains significant ($B = -.46$, SD $= .17$; Wald $\chi^2(1, N = 116) = 7.40$, $p < .01$). Similarly, for choice quality, the number of alternatives is no longer significant ($F(1, 116) = .04$, NS [one-tailed]), but the amount of information remains significant ($F(1, 116) = 29.01$, $p < .001$).

Planned comparisons show that although increasing the number of alternatives in a choice set can sometimes lead to information overload, the same increase in the number of alternatives does not lower decision quality when the amount of information in a choice set is not increased. For example, although the dominant calculator was less likely to be chosen in the 27-alternative-even distribution (52.75 bit) condition than in the 18-alternative-uneven distribution (36.28 bit) condition (adjusted proportions $= 0.35$ and 0.68, $z = 2.54$, $p < .01$) and less likely to be considered for purchase (adjusted proportions $= 0.50$ and 0.79, $z = 2.27$, $p < .05$), it was not significantly less likely to be chosen in the 27-alternative-uneven distribution (41.37 bit) condition than in the 18-alternative-even distribution (46.26 bit) condition (adjusted proportions $= 0.56$ and 0.58, $z = .16$, NS), or less likely to be considered for purchase (adjusted proportions $= 0.70$ and 0.55, $z = 1.21$, NS). Although relative choice quality was significantly lower in the 27-alternative-even distribution (52.75 bit) condition than in the 18-alternative-uneven distribution (36.28 bit) condition (M's $= .65$ and $.96$; $F(1, 112) = 24.06$, $p < .0001$), choice quality was actually significantly higher in the 27-alternative-uneven distribution (41.37 bit) condition than in the 18-alternative-even distribution (46.26 bit) condition (M's $= .95$ and $.78$; $F(1, 112) = 7.36$, $p < .01$), suggesting that more alternatives may sometimes be associated with less information and higher choice quality. Together these results show that information structure, not the number of alternatives, is the crucial factor in determining overload.

Discussion

Results from study 1 show that information structure is a better predictor of information overload than simple counts of alternatives. The structural approach encompasses simple counts, thus accounting for traditional findings that an increase in the number of alternatives in a choice set can lead to declines in decision quality. At the same time, the structural approach also accounts for other dimensions that affect the amount of information in a choice set. This more thorough accounting allows the structural approach to predict when the same increase in the number of alternatives will not lead to overload. In addition, the structural approach shows that overload may occur even if there is no change in the number of attributes or alternatives in a choice set. One way that this may occur is if the distribution of attribute levels across alternatives becomes more uniform.

STUDY 2

Study 2 extends study 1 by examining the effect of information structure on decision outcomes and information acquisition in a process tracing experiment. Study 2 also uses a within-subjects design that provides a strong test of adaptive behavior (Payne et al. 1988). Importantly, study 2 manipulates information structure while holding both the number of alternatives and the number of attributes constant.

Experimental Procedure

Design and Task. In study 2, participants acquired information and chose a calculator for a friend using an information acquisition system similar to Mouselab (Bettman et al. 1990; Creyer et al. 1990; Payne et al. 1988). Participants made choices among 24 sets of calculators. In study 2, neither the number of attributes nor the number of alternatives was used to manipulate information structure; in each choice set there were 16 alternatives defined by eight attributes. Information structure was manipulated at four levels, with six repetitions at each level, through the number of attribute levels and the distribution of attribute levels across alternatives. Four lottery prizes of $25 were offered as incentives for participants to make the "best" choice. In order to prevent ceiling effects and ensure that there would be "information overload," participants were given only one minute for each choice. Because dominant alternatives are rare in most consumer environments, dominant alternatives were not used in this study.

Twenty-seven undergraduate students (juniors and seniors) participated in the study. Participants were told that they wanted to buy a calculator for a friend's birthday. A recent *Consumer Reports* article suggested eight dimensions to consider when buying a calculator: versatility, ease of use, battery life, warranty, weight, memory, screen quality, and features. Calculators were rated on these dimensions on a scale from zero to 1,000, where 1,000 is best. To help participants in their decision, their friend had indicated the importance of these dimensions on a scale from zero to 100, where 100 was the most important. Participants were told to use these weights in their decisions. Participants were given practice using the information acquisition system and were told that they had decided to buy the calculator from Electronics USA, an online retailer. They were also told that they would be making 24 choices and would have 60 seconds to make each choice.

Information Acquisition System. A computer-based information acquisition system similar to Mouselab (Bettman et al. 1990; Creyer et al. 1990; Payne et al. 1988) was developed specifically for this study. The first row contained attribute weights for the eight attributes. Attribute weights were selected by independent draws from a uniform distribution and were rescaled to sum to 100 (Johnson and Payne 1985; Payne et al. 1988). The next 16 rows contained the attribute values for each alternative. At the bottom of the screen, participants could select their preferred alternative among the 16 available alternatives. At the top of the screen a timer showed the time remaining for a particular decision, and an indicator showed the decision number.

Information about attribute weights and attribute values was hidden behind opaque boxes. Moving the mouse cursor over a box revealed its contents, and the information remained visible until the cursor was moved out of the box. The information was available for only one box at a time. Participants could open as many boxes as many times as they wished. After 60 seconds, moving the mouse over the boxes no longer revealed information, and a message appeared asking participants to "please make a choice." The information acquisition system recorded the number of boxes opened, the order and time they were opened, the total elapsed time associated with a particular decision, and the final choice.

Each participant made 24 choices (four information structure conditions times six replications). The first 12 choice sets contained three replications of the four information structure conditions. Within each block of 12 choice sets, the order of alternatives within the set, as well as the order of choice sets within the block, was randomized with the same order for all participants. See Creyer et al. (1990) and Payne et al. (1988) for similar procedures.

Experimental Variable

Information Structure. Information structure was manipulated at four levels through the number of attribute levels and the distribution of attribute levels across alternatives. Twenty-four choice sets consisting of 16 alternatives and eight attributes were created. Depending on the condition, there were two or four attribute levels. This manipulation is different from previous information acquisition research (Bettman et al. 1990, 1993; Creyer et al. 1990; Payne et al. 1988) in which the number of attribute levels for any attribute equaled the number of alternatives. When there were two attribute levels, two values were randomly chosen for each attribute from a uniform distribution ranging from zero (least preferred) to 1,000 (most preferred). When there were four attribute levels, four values were randomly chosen for each attribute.

When attribute levels were evenly distributed across alternatives and there were two attribute levels, one attribute value was shared by eight of the alternatives, and the other by the remaining eight alternatives. When there were four attribute levels, each of the four attribute values was shared by four of the alternatives. When attribute levels were unevenly distributed and there were two attribute levels, one attribute value was shared by 14 of the 16 alternatives, and the other by two of the 16 alternatives. When there were four attribute levels, one of the attribute values was shared by 10 of the 16 alternatives, and the other three attribute levels were each shared by two of the remaining six alternatives. As in study 1, the potential effects of attribute skew were controlled by having the majority of alternatives share the highest attribute value for four of the attributes and by having the majority of alternatives share the lowest attribute value for the remaining four attributes. This suggests that in the uneven distribution condition, half the attributes were less diagnostic and half the attributes were more diagnostic of the best alternative than when the attribute levels were evenly distributed (Van Wallendael and Guignard 1992).

Because it is impossible to change the number of levels of an attribute without simultaneously changing the distribution of attribute levels, the manipulations are nonorthogonal. This means that the effects of the number of attribute levels and the distribution of attribute levels across alternatives should be judged in terms of their combined effect on the total amount of information in a choice set. The manipulations created information environments with 17.39 bits in the two attribute level–uneven distribution condition, 32.00 bits in the two attribute level–even distribution condition, 49.56 bits in the four attribute–uneven distribution condition, and 64.00 bits in the four attribute level–even distribution condition. In study 2, mean interattribute correlations were similar but directionally more positive in the even (high information) than in the uneven (low information) distribution conditions (r's = .05 and .01, NS). Because choice sets with positively correlated attributes are associated with higher quality decisions (Bettman et al. 1993), this represents a stronger test of hypothesis 1a. Note also that simple counts of alternatives and attributes predict no differences among the choice sets since all choice sets contain 16 alternatives and eight attributes.

Dependent Measures

Seven dependent measures were collected for this study: decision quality, the number of acquisitions, the average time per acquisition, the proportion of time spent on the most important attribute, the variance in time spent per attribute, the variance in time spent per alternative, and the amount of alternative versus attribute-based processing. See Payne et al. (1993) for a review of these and other measures of decision-making outcomes and processes.

Decision Quality. Decision quality was assessed as in

TABLE 2

STUDY 2: MEANS AND STANDARD DEVIATIONS OF DEPENDENT MEASURES

	Two attribute levels		Four attribute levels	
	Uneven distribution (17.39 bits)	Even distribution (32.00 bits)	Uneven distribution (49.56 bits)	Even distribution (64.00 bits)
Choice quality[a]	.87 (.03)	.80 (.03)	.77 (.04)	.74 (.05)
Number of acquisitions	168.5 (8.7)	164.8 (9.8)	149.0 (9.3)	141.3 (7.4)
Average time per acquisition (seconds)	.199 (.008)	.214 (.009)	.211 (.009)	.220 (.010)
Proportion of time on most important attribute	.31 (.02)	.28 (.03)	.34 (.04)	.35 (.04)
Variance in proportion of time per attribute	.0062 (.0011)	.0080 (.0011)	.0114 (.0019)	.0085 (.0013)
Variance in proportion of time per alternative	.0004 (.0001)	.0005 (.0001)	.0004 (.0001)	.0009 (.0002)
Acquisition pattern[b]	−.62 (.04)	−.44 (.04)	−.54 (.05)	−.53 (.05)
Percent of unique cells examined	.54 (.02)	.51 (.02)	.47 (.02)	.46 (.02)
Amount of information experienced (bits)[c]	9.44 (.35)	16.18 (.59)	23.12 (1.04)	29.57 (1.09)

NOTE.—The number of bits (amount of information) in each condition is determined by the number and distribution of attribute levels. Standard deviations are given in parentheses.
[a]Quality of choice relative to the best and worst alternatives in the choice set.
[b]Index of the relative amount of attribute (−) vs. alternative-based (+) processing.
[c]Percentage of unique cells examined multiplied by the amount of information in each choice set.

study 1 by comparing the utility of the chosen alternative to the utilities of the best and worst choices in each choice set. Because dominant alternatives were not present in study 2, probabilities of consideration and choice were not calculated.

Acquisitions. To determine how information structure in a choice set of fixed size affects information acquisition, the number of acquisitions and the amount of time spent acquiring information were measured. These measures were used to calculate the average amount of time per acquisition.

Processing Selectivity. To assess how information structure affects selectivity in processing, the proportion of time spent acquiring information about the most important attribute and the variance in time spent acquiring information about alternatives and attributes were measured (Bettman et al. 1993; Creyer et al. 1990; Payne et al. 1988). To normalize the variance associated with positively skewed time data and to limit the effects of outliers, time values were transformed by taking logs and observations more than three standard deviations away from the mean and were not included in the variance of proportions analysis (West 1996; Winer, Brown, and Michels 1991).

Acquisition Pattern. Although no specific prediction of attribute versus alternative-based acquisition was made, an index of attribute versus alternative-based transitions was created by taking the number of alternative-based transitions minus the number of attribute-based transitions and then dividing by the sum of alternative- and attribute-based transitions (Payne 1976). This index ranges from −1 (indicating only attribute-based processing) to +1 (indicating only alternative-based processing).

Results

Table 2 provides the means and standard deviations for the dependent measures as a function of information structure. Of the 27 participants, four did not take the task seriously: they did not gather any information (open any boxes) for at least one of the 24 decisions and, therefore, were not included in the analysis. The mean quality of participants' choices was fairly high ($M = .80$). On average, participants made 156 acquisitions per choice set with an average time per acquisition of .21 seconds, and they spent 32% of their time acquiring information on the most important attribute. In addition, participants generally processed information by attribute rather than by alternative ($M = -.53$). A MANOVA on the seven dependent measures reveals a significant effect of information structure (Wilks's $\lambda = .193$, $F(21, 172.8) = 6.37$, $p < .0001$). A separate MANOVA analysis shows a significant effect of the distribution of attribute levels (Wilks's $\lambda = .20$, $F(7, 16) = 8.98$, $p < .001$) and the number of attribute levels (Wilks's $\lambda = .12$, $F(7, 16) = 16.99$, $p < .0001$), as well as a significant interaction between attribute distribution and the number of attribute levels (Wilks's $\lambda = .27$, $F(7, 16) = 6.22$, $p < .001$).

Decision Quality. As in study 1, ANOVA results show that an increase in the amount of information in a choice set led to declines in decision quality: (M's $= .87, .80, .77$, and $.74$) in the 17.39, 32.00, 49.56, and 64.00 bit conditions, respectively ($F(3, 66) = 6.48$, $p < .001$). Trend analysis shows a significant linear effect for information structure ($F(1, 22) = 13.73$, $p < .001$). Higher-order effects were not significant. Support was found for hypothesis 1a, that the even distribution of attribute levels lowers decision quality relative to the uneven distribution of attribute levels (M's $= .77$ and $.82$; $F(1, 22) = 30.29$, $p < .0001$, $\eta_p^2 = .58$), as well as hypothesis 1b, that an increase in the number of attribute levels lowers decision quality (M's $= .76$ and $.84$; $F(1, 22) = 9.34$, $p < .01$, $\eta_p^2 = .30$). The interaction between attribute distribution and the number of attribute levels was not significant ($F(1, 22) = .65$, NS).

Acquisitions. The ANOVA results show that increasing amounts of information generally increased the time per acquisition (M's $= .199, .214, .211$, and $.220$) in the 17.39, 32.00, 49.56, and 64.00 bit conditions, respectively ($F(3, 66) = 7.80$, $p < .0001$) and decreased the number of acquisitions (M's $= 168.5, 164.8, 149.0$, and 141.3) in the 17.39, 32.00, 49.56, and 64.00 bit conditions, respectively ($F(3, 66) = 8.65$, $p < .0001$). Trend analysis shows significant linear effects for time per acquisition ($F(1, 22) = 18.44$, $p < .0001$) and the number of acquisitions ($F(1, 22) = 24.36$, $p < .0001$). Higher-order effects were not significant. Support was found for hypothesis 3a, that the even relative to the uneven distribution of attribute levels increases the average time per acquisition (M's $= .217$ and $.205$; $F(1, 22) = 11.88$, $p < .01$, $\eta_p^2 = .35$), and marginal support was found for hypothesis 3b, that the even distribution of attribute levels lowers the number of acquisitions (M's $= 153.1$ and 158.8; $F(1, 22) = 2.51$, $p < .07$ [one-tailed], $\eta_p^2 = .10$). Support was found for hypotheses 4a and 4b, that increasing the number of attribute levels from two to four increases the average time per acquisition (M's $= .216$ and $.205$; $F(1, 22) = 10.56$, $p < .01$, $\eta_p^2 = .32$) and decreases the number of acquisitions (M's $= 145.2$ and 166.7; $F(1, 22) = 17.92$, $p < .001$, $\eta_p^2 = .45$).

Processing Selectivity. Results show that increasing amounts of information generally led to an increase in the proportion of time spent on the most important attribute (M's $= .31, .28, .34$, and $.35$) in the 17.39, 32.00, 49.56, and 64.00 bit conditions, respectively ($F(3, 66) = 3.15$, $p < .05$), increased variance in the proportion of time spent per attribute (M's $= .0062, .0080, .0114$, and $.0085$) in the 17.39, 32.00, 49.56, and 64.00 bit conditions, respectively ($F(3, 66) = 5.91$, $p < .001$), and increased variance in the proportion of time spent per alternative (M's $= .0004$, $.0005$, $.0005$, and $.0009$) in the 17.39, 32.00, 49.56, and 64.00 bit conditions, respectively ($F(3, 66) = 5.14$, $p < .01$). Mixed support was found for hypothesis 5a, that the even distribution of attribute levels increases processing selectivity. The even relative to the uneven distribution of attribute levels does not have a significant effect on the proportion of time spent on the most important attribute (M's $= .31$ and $.33$; $F(1, 22) = 1.66$, NS) or the variance in time spent per attribute (M's $= .0083$ and $.0088$; $F(1, 22) = .36$, NS), but does significantly increase the variance in time spent per alternative (M's $= .0007$ and $.0004$; $F(1, 22) = 7.05, p < .01, \eta_p^2 = .24$). Support was found for hypothesis 5b, that increasing the number of attribute levels increases processing selectivity. In particular, increasing the number of attribute levels increases the proportion of time spent on the most important attribute (M's $= .34$ and $.30$; $F(1, 22) = 7.98$, $p < .01$, $\eta_p^2 = .27$), increases the variance in time spent per attribute (M's $= .0100$ and $.0071$; $F(1, 22) = 8.87$, $p < .01$, $\eta_p^2 = .29$), and increases the variance in time spent per alternative (M's $= .0007$ and $.0005$; $F(1, 22) = 5.82$, $p < .05$, $\eta_p^2 = .21$).

Acquisition Pattern. Although participants generally processed by attribute in all conditions, the pattern of acquisitions differed across conditions (M's $= -.62, -.44, -.54$, and $-.53$) in the 17.39, 32.00, 49.56, and 64.00 bit conditions, respectively ($F(3, 66) = 16.77, p < .0001$). The even relative to the uneven distribution of attribute levels leads to relatively greater processing by alternative (M's $= -.49$ and $-.58$; $F(1, 22) = 26.94$, $p < .001$, $\eta_p^2 = .55$). The number of attribute levels has no significant effect on acquisition pattern (M's $= -.54$ and $-.53$; $F(1, 22) = .20$, NS).

Additional Analysis: Amount of Information Experienced. To examine how information structure affects the amount of information actually experienced by the decision maker, two additional measures of processing were examined.[1] The first is the percentage of unique cells (out of the 128 available) that were examined. The second is the percentage of unique cells multiplied by the amount of information available in each choice set. The ANOVA results show that increasing amounts of information led to a decrease in the percentage of unique cells examined (M's $=$ 54%, 51%, 47%, and 46%) in the 17.39, 32.00, 49.56, and 64.00 bit conditions, respectively ($F(3, 66) = 12.51$, $p < .0001$) but an increase in the amount of information experienced (M's $= 9.44$ bits, 16.18 bits, 23.12 bits, and 29.57 bits) in the 17.39, 32.00, 49.56, and 64.00 bit conditions, respectively ($F(3, 66) = 269.40$, $p < .0001$). The even relative to the uneven distribution of attribute levels decreased the percentage of unique cells examined (M's $=$ 48% and 51%; $F(1, 22) = 6.08, p < .03, \eta_p^2 = .22$) and increased the amount of information experienced (M's $= 22.88$ bits and 16.28 bits; $F(1, 22) = 342.06$, $p < .0001$, $\eta_p^2 = .94$). Similarly, an increase in the number of attribute levels decreased the percentage of unique cells examined (M's $=$ 46% and 52%; $F(1, 22) = 19.64, p < .0001, \eta_p^2 = .47$) and increased the amount of information experienced (M's $= 26.34$ bits and 12.81 bits; $F(1, 22) = 306.31$, $p < .0001$, $\eta_p^2 = .93$).

[1]Thanks to a reviewer for this suggestion.

Discussion

Results from study 2 provide additional support for the idea that information structure affects information overload and that structural elements, such as the number and distribution of attribute levels, can affect decision quality even if the number of alternatives and attributes in a choice set are held constant. Study 2 also provides insight into the process through which information structure affects decision quality. In particular, study 2 suggests that choice sets that contain more information per element are also associated with fewer acquisitions and more time per acquisition. Because fewer information elements are acquired, decision-making quality declines. To the extent that choice sets that contain more information are also more diagnostic, these results are consistent with previous research that shows that increased diagnosticity lowers information acquisition (Van Wallendael and Guignard 1992). One explanation is that choice sets that contain more information decrease confidence thresholds or concern about confidence thresholds. Future research should examine these possibilities by measuring choice confidence.

Study 2 also shows that increased amounts of information lead consumers to be more selective in their information acquisition (e.g., spend a larger proportion of time on the most important attribute). This means that they are less likely to process all of the information and therefore less likely to choose the best alternative in a set. Given that studies 1 and 2 show that information structure affects information overload and information acquisition, it is important to examine potential moderators of the relationship among information structure, the amount of information processing, and information overload.

STUDY 3: SIMULATION

Previous research has shown that the impact of the number of alternatives and number of attributes on decision effort without time pressure and decision quality under time pressure depends on the decision strategy used. In particular, Monte-Carlo simulations have shown that an increase in the number of alternatives and attributes in a choice set has a more dramatic impact on information acquisition and decision quality for compensatory decision rules than noncompensatory decision rules (Payne et al. 1993).

At the same time previous simulation research on decision strategies has not examined the effect of information structure, including the number and distribution of attribute levels, on decision effort and decision quality. In previous studies, the number of attribute levels has equaled the number of alternatives, and attribute levels have been evenly distributed across alternatives (Bettman et al. 1993; Creyer et al. 1990; Johnson and Payne 1985; Payne et al. 1988).

To explore further the potential relationship among information structure, information processing, and decision making, a Monte-Carlo experimental simulation (Hastie and Stasser 2000; Payne et al. 1993) was conducted. In study 2, the effects of information structure on decision quality and information acquisition (i.e., consumers' adaptive behavior) were measured. In the simulation, decision processes were manipulated explicitly through the decision rules of an idealized consumer, and the amount of information processing was measured through elementary information processes (EIPs; Payne et al. 1988). This allows the interaction between information structure and decision processes to be examined.

Method

Procedure and Experimental Variables. The information structure was manipulated through the number of alternatives (eight or 16), the number of attributes (four or eight), the number of attribute levels (two or four), and the distribution of attribute levels across alternatives (even or uneven). Unlike previous simulation research (Bettman et al. 1993; Creyer et al. 1990; Payne et al. 1988), the number of attribute levels was manipulated independently rather than being equal to the number of alternatives. When there were two attribute levels, two values were randomly chosen for each attribute from a uniform distribution ranging from zero to 1,000. When there were four attribute levels, four values were randomly chosen for each attribute. Attribute levels were randomly permutated across alternatives for each attribute. Attribute weights were randomly generated from a uniform distribution ranging from zero to one and normalized to sum to one (Johnson and Payne 1985; Payne et al. 1988).

When attribute levels were evenly distributed, each attribute level occurred the same number of times. When two attribute levels were unevenly distributed, three-quarters of the alternatives had one level of an attribute and one-quarter of the alternatives had the other level. When four attribute levels were unevenly distributed, five-eighths of the alternatives had the first level, one-eighth had the second level, one-eighth had the third level, and one-eighth had the fourth level. In the uneven condition, the best alternative shared the same attribute level as the majority of alternatives for one-half of the attributes and the same attribute level as the minority of alternatives for one-half of the attributes. Mean interattribute correlations were not significantly different in the even ($M = -.038$) and uneven ($M = -.034$) distribution conditions ($F(1, 2{,}398) = 1.02$, NS). As in study 2, the manipulations of the number of attribute levels and the distribution of attribute levels are nonorthogonal since they cannot be changed independently from one another. This means that the impact of these variables should be interpreted in terms of their combined effect on information structure.

To study how information structure affects the relationship between the amount of information processing (EIPs) and decision quality, time pressure was manipulated at two levels. In the no-time-pressure condition, no limit was placed on the number of EIPs used in choice. In the time-pressure conditions, decision rules were constrained to 64 EIPs. This limit, based on previous research (Payne et al. 1988), was

12.5% of the maximum number of EIPs required for the weighted additive model with no time pressure. Note that, as in previous research, the time-pressure condition assumes that any given EIP (e.g., a read) takes the same amount of time regardless of information structure. Results from study 2 question this assumption.

Five decision strategies (WADD, LEX, SAT, EBA, and MCD) were applied to each information environment (Johnson and Payne 1985; Payne et al. 1988). Based on preliminary simulation runs, cutoff levels of 300 and 500 were set for the satisficing (SAT) and elimination by aspects (EBA) rules, respectively. The experimental manipulations created 160 experimental cells per simulation run. Based on the size of previous simulations (Johnson and Payne 1985; Payne et al. 1988), the simulation was run 50 times to create 8,000 observations.

Dependent Variables

Amount of Information Processing. The amount of information processing was measured as the sum of EIPs—reads, products, additions, comparisons, differences, and eliminations (Johnson and Payne 1985; Payne et al. 1988).[2]

Choice Quality. Choice quality was measured as the utility of the chosen alternative relative to the expected value of random choice, where the expected value of random choice is the average utility of all alternatives in the choice set (Johnson and Payne 1985; Payne et al. 1988). This scale equals one if the best alternative is chosen and zero for random choice.

Results

Amount of Information Processing. The ANOVA results from the no-time-pressure condition show that an increase in the amount of information in a choice set increased the number of EIPs ($B = 5.72$; $F(1, 3{,}990) = 1{,}582.01$, $p < .0001$, $\eta_p^2 = .28$). There was also a main effect of decision strategy on the number of EIPs ($F(4, 3{,}990) = 44.10$, $p < .0001$, $\eta_p^2 = .04$) as well as a significant interaction between the amount of information in the choice set and decision strategy ($F(4, 3{,}990) = 302.07$, $p < .0001$, $\eta_p^2 = .23$). An increase in the number of alternatives increased EIPs (M's $= 102.04$ and 197.80) in the eight- and 16-alternative conditions, respectively ($F(1, 3{,}920) = 26{,}339.51$, $p < .0001$, $\eta_p^2 = .87$) as did an increase in the number of attributes (M's $= 106.06$ and 193.78) in the four- and eight-attribute conditions, respectively ($F(1, 3{,}920) = 22{,}100.27$, $p < .0001$, $\eta_p^2 = .85$). The even distribution of attribute levels slightly increased the number of EIPs to the uneven condition (M's $= 150.59$ and 149.24; $F(1, 3{,}920) = 5.24$, $p < .03$, $\eta_p^2 = .001$). An increase in the number of attribute levels slightly decreased the number of EIPs (M's $= 150.62$ and 149.22) in the two-level and four-level conditions, respectively ($F(1, 3{,}920) = 5.66$, $p < .02$, $\eta_p^2 = .001$).

The significant interaction between the distribution of attribute levels and decision strategy ($F(4, 3{,}920) = 6.67$, $p < .001$, $\eta_p^2 = .007$) shows that decision strategy moderates the effect of the distribution of attribute levels on EIPs. The even distribution of attribute levels raised the number of EIPs for the MCD strategy (M's $= 246.41$ and 253.37; $F(1, 3{,}920) = 27.81$, $p < .0001$, $\eta_p^2 = .007$) but had no significant effect on the LEX (M's $= 76.45$ and 74.41; $F(1, 3{,}920) = 2.40$, NS), SAT (M's $= 49.42$ and 51.13; $F(1, 3{,}920) = 1.69$, NS), EBA (M's $= 86.95$ and 87.07; $F(1, 3{,}920) = .01$, NS), or WADD strategies (M's $=$ 287.00 and 287.00; $F(1, 3{,}920) = .00$, NS) in the uneven and even distribution conditions, respectively.

The significant interaction between the number of attribute levels and decision strategy ($F(4, 3{,}920) = 71.82$, $p < .0001$, $\eta_p^2 = .068$) shows that decision strategy also moderates the effect of the number of attribute levels on EIPs. In particular, an increase in the number of attribute levels raised the number of EIPs for the MCD strategy (M's $= 243.45$ and 256.33; $F(1, 3{,}920) = 95.26$, $p < .0001$, $\eta_p^2 = .024$) and lowered the number of EIPs for the LEX strategy (M's $= 84.63$ and 66.23; $F(1, 3{,}920) = 194.44$, $p < .0001$, $\eta_p^2 = .047$) in the two- and four-level attribute conditions, respectively. The number of attribute levels marginally increased EIPs for the SAT strategy (M's $= 51.40$ and 49.15; $F(1, 3{,}920) = 2.91$, $p < .09$, $\eta_p^2 = .001$) and had no significant effect on the EBA (M's $= 87.63$ and 87.39; $F(1, 3{,}920) = .33$, NS) or WADD strategies (M's $= 287.00$ and 287.00; $F(1, 3{,}920) = .00$, NS) in the two-level and four-level attribute conditions, respectively.

Decision Quality. The simulation assumes, as in previous research (Bettman et al. 1990; Johnson and Payne 1985; Payne et al. 1988), that any given EIP takes the same amount of time regardless of information structure. Under this assumption, ANOVA results show that an increase in the amount of information lowered decision quality under time pressure ($B = -.00074$; $F(1, 3{,}990) = 34.67$, $p < .0001$, $\eta_p^2 = .009$). There was also a significant effect of decision strategy on relative decision quality ($F(4, 3{,}990) = 28.50$, $p < .0001$, $\eta_p^2 = .028$) as well as a significant interaction between information structure and decision strategy ($F(4, 3{,}990) = 5.71$, $p < .001$, $\eta_p^2 = .006$). An increase in the number of alternatives lowered decision quality (M's $= .49$ and $.38$) in the eight- and 16-alternative conditions, respectively ($F(1, 3{,}920) = 44.82$, $p < .0001$, $\eta_p^2 = .011$) as did an increase in the number of attributes (M's $= .53$ and $.34$) in the four- and eight-attribute conditions, respectively ($F(1, 3{,}920) = 136.46$, $p < .0001$, $\eta_p^2 = .034$). The even distribution of attribute levels increased relative decision quality (M's $= .41$ and $.45$) in the uneven and even attribute distribution conditions, respectively ($F(1, 3{,}920) = 6.32$, $p < .02$, $\eta_p^2 = .002$) when EIPs were constrained. An increase in the number of attribute levels also increased relative decision quality (M's $= .39$

[2]Weighting EIPs by response times (Bettman et al. 1990) led to similar results.

and .47) in the two- and four-level attribute conditions, respectively ($F(1, 3{,}920) = 24.21$, $p < .0001$, $\eta_p^2 = .006$).

The significant interaction between the number of attribute levels and decision strategy ($F(4, 3{,}920) = 3.80$, $p < .01$, $\eta_p^2 = .004$) shows that decision strategy also moderates the effect of the number of attribute levels on decision quality. In particular, an increase in the number of attribute levels raised decision quality for the MCD (M's = .27 and .42; $F(1, 3{,}920) = 15.39$, $p < .0001$, $\eta_p^2 = .004$) and the EBA strategies (M's = .30 and .47; $F(1, 3{,}920) = 19.36$, $p < .0001$, $\eta_p^2 = .005$) in the two- and four-attribute-level conditions, respectively. An increase in the number of attribute levels marginally increased decision quality for the LEX strategy (M's = .56 and .63; $F(1, 3{,}920) = 3.37$, $p < .07$, $\eta_p^2 = .001$) but had no significant effect on the SAT (M's = .26 and .30; $F(1, 3{,}920) = 1.23$, NS) or WADD strategies (M's = .56 and .55; $F(1, 3{,}920) = .07$, NS) in the two- and four-level attribute conditions, respectively. The interaction between the distribution of attribute levels and decision strategy was not significant ($F(4, 3{,}920) = .56$, NS).

Mediation Analysis. Using the corresponding EIP counts from the no-time-pressure condition to predict decision quality under time pressure, in a model that controls for decision strategy, shows a significant effect of EIPs ($B = -.00094$; $F(1, 3{,}994) = 92.08$, $p < .0001$, $\eta_p^2 = .023$). As mentioned above, a separate analysis shows a significant effect of information structure on decision quality under time pressure ($B = -.00074$; $F(1, 3{,}990) = 34.67$, $p < .0001$, $\eta_p^2 = .009$). When EIPs are added as a covariate to this model, the effect of information structure on choice quality is no longer significant ($B = .0056$; $F(1, 3{,}989) = .12$, NS), but EIPs remain significant ($B = -.0011$; $F(1, 3{,}989) = 77.15$, $p < .0001$, $\eta_p^2 = .019$). These results show that the amount of information processing (EIPs) without time pressure perfectly mediates the relationship between information structure and decision quality under time pressure (Baron and Kenny 1986).

Discussion

Results from the simulation provide additional insights into the relationship among information structure, information processing, and decision making. Like the experimental studies, the simulation shows that increased amounts of information $I(A)$ lead to declines in decision quality. The simulation also shows that the relationship between information structure and information overload depends on the decision rule used, with information structure having a greater effect under certain decision rules (e.g., MCD) than others (e.g., WADD). Despite these differences, increasing amounts of information led to significant declines in decision quality under time pressure regardless of the rule used.

More important, the simulation helps explain the relationship among information structure, the amount of information processing (EIPs), and information overload. In particular, greater amounts of information lead to greater information processing, which in turn lead to greater declines in decision quality under time pressure. By showing that EIPs mediate the relationship between information structure and decision quality, the simulation helps explain the process through which changes in information structure can lead to information overload.

GENERAL DISCUSSION

Almost 30 years ago, William Wilkie (1974, p. 465) noted that "*information* itself has not been carefully defined for the consumer environment. . . . Clearly, however, marketing research will have to grapple with this zone of inquiry in the future." Now, in the age of the Internet, developing an understanding of how information-rich environments affect consumer decision making is of crucial importance. Given the disparate ways in which information can be presented to consumers and the high potential for information overload in online environments, it is important to use measures that capture the multiple dimensions of information. Structural measures of information, such as those from information theory, offer a way to capture these dimensions and predict information overload more effectively. A structural approach suggests that the number of alternatives and attributes in a choice set are just two potential determinants of the amount of information in a choice set. Other dimensions, such as the number of attribute levels and the distribution of those levels across alternatives, can also play an important role in determining the amount of information associated with a set of alternatives.

Importantly, structural measures of information encompass the frequency-based approaches traditionally used in marketing but also provide different predictions than traditional approaches. Contrary to what is found by merely counting the number of alternatives and attributes in an information environment, accounting for the distribution and number of attribute levels suggests that more alternatives do not necessarily mean more information. Study 1 examines the potential benefits of using formal measures of information structure by creating conditions that replicate previous findings, in which more alternatives lead to declines in decision quality, but also by creating conditions in which the same increase in the number of alternatives does not lead to overload. Results of this study contradict previous studies (e.g., Jacoby et al. 1974a, 1974b; Keller and Staelin 1987; Malhotra 1982; Scammon 1977) that suggest that the probability of overload can only increase for choice sets with more alternatives (attributes), when the number of attributes (alternatives) is held constant.

Study 2 provides additional insights into the relationship between information structure and information overload by measuring information acquisition as well as decision quality. In particular, study 2 shows that consumers adapt their acquisition of information in response to changes in information structure. When a choice set contains more information per element, fewer acquisitions are made, more time is spent per acquisition, and consumers are more selective in their information acquisition. Study 2 also shows that a change in information structure that increases the amount of information in a choice set can lead to declines in decision quality—even if there is no change in the number of attributes or alternatives.

Study 3, a Monte-Carlo simulation, helps illustrate the link among information structure, the amount of information processing, and decision quality by applying different decision rules to multiple information environments. Results from this study show that information structure affects information processing (EIPs) and decision quality, but that these effects depend on which decision strategy is used. More importantly, study 3 shows that increasing the amount of information in a choice set leads to increased information processing (EIPs), and this increase in processing mediates the relationship between information structure and information overload. As such, this series of studies builds an important conceptual link between research on information overload (Jacoby et al. 1974a, 1974b; Keller and Staelin 1987; Malhotra 1982) and research on decision processes (Bettman et al. 1990; Creyer et al. 1990; Johnson and Payne 1985; Payne et al. 1988).

In addition to linking related streams of research, this article provides novel insights that can inform researchers who are interested in decision outcomes as well as those who are interested in decision processes. For example, neither of these streams of research has considered how structural elements, such as the number and distribution of attribute levels, affect decision outcomes or processes. This research suggests that these elements should be considered, particularly in environments in which information overload is likely. For those who are interested in decision outcomes, results from this research question the assumption that more alternatives necessarily mean more information and a greater likelihood of information overload. Similarly, results from study 2, in which increased amounts of information were found to increase time per acquisition, bring into question the assumption that processing speeds are constant for a given EIP within a given environment (Bettman et al. 1990; Johnson and Payne 1985; Payne et al. 1988).

Before discussing future research, it is important to point out the limitations of this research. It should be noted that these findings are from studies that experimentally control for multiple environmental and individual factors that may affect information overload in real choice settings. For example, in order to control for experience effects, novel stimuli and environments were used. In the real world, decision makers often draw on their knowledge of product categories. Product category experience and expertise may change consumers' processing of information and affect the extent to which they are overloaded with information (Alba and Hutchinson 1987). In addition, the convenience samples used in this research are by no means representative of the U.S. population as a whole. At the same time, product categories were chosen to be of interest to participants, and the participants were provided with financial incentives to make good choices. The congruent results across the three studies, two experiments, and simulation provide additional confidence in the results.

There are a number of potential avenues for future research, including an examination of mechanisms for reducing information overload, as well as research that examines the potential impact of information overload on the quality of consumers' lives (Mick 2003). Other research could examine the interplay between information structure, which as a task variable does not depend on particular data values, and context variables, such as the relative importance of attributes to decision makers, the presence of dominant alternatives, positive versus negative interattribute correlation, and the diagnosticity of information (e.g., Bettman et al. 1993; Payne et al. 1988; Van Wallendael and Guignard 1992). Developing measures that assess the combined effects of task and context variables on decision-making processes and outcomes may be particularly important. Just as structural measures enhance our ability to predict information overload in diverse information environments that cannot be compared using traditional approaches in marketing, other measures may provide important insights into an increasingly information-based consumer experience.

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REFERENCES

Alba, Joseph W. and J. Wesley Hutchinson (1987), "Dimensions of Consumer Expertise," *Journal of Consumer Research,* 13 (March), 411–454.

Baron, Reuben M. and David A. Kenny (1986), "The Moderator-Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations," *Journal of Personality and Social Psychology,* 51 (December), 1173–1182.

Bettman, James R., Eric J. Johnson, Mary Frances Luce, and John W. Payne (1993), "Correlation, Conflict and Choice," *Journal of Experimental Psychology: Learning, Memory, and Cognition,* 19 (4), 931–951.

Bettman, James R., Eric J. Johnson, and John W. Payne (1990), "A Componential Analysis of Cognitive Effort in Choice," *Organizational Behavior and Human Decision Processes,* 45 (February), 111–139.

Biehal, Gabriel and Dipankar Chakravarti (1983), "Information Accessibility as a Moderator of Consumer Choice," *Journal of Consumer Research,* 10 (June), 1–14.

Creyer, Elizabeth H., James R. Bettman, and John W. Payne (1990), "The Impact of Accuracy and Effort Feedback and Goals on Adaptive Decision Behavior," *Journal of Behavioral Decision Making,* 3 (1), 1–16.

Dawes, Robyn M. (1970), "Information Theory," in *Mathematical Psychology,* ed. Clyde H. Coombs, Robyn M. Dawes, and Amos Tversky, Englewood Cliffs, NJ: Prentice-Hall, 307–350.

Garner, Wendell R. (1962), *Uncertainty and Structure as Psychological Concepts,* New York: Wiley.

Gensch, Dennis H. and Ehsan S. Soofi (1995), "Information-Theoretic Estimation of Individual Consideration Set," *International Journal of Research in Marketing,* 12 (May), 25–38.

Glazer, Rashi (1984), "Multiattribute Perceptual Bias as Revealing of Preference Structure," *Journal of Consumer Research,* 11 (June), 510–521.

Hastie, Reid and Garold Stasser (2000), "Computer Simulation Methods for Social Psychology," in *Handbook of Research Methods in Social and Personality Psychology,* ed. Harry T. Reis and Charles M. Judd, New York: Cambridge University Press, 85–114.

Herniter, Jerome D. (1973), "An Entropy Model of Brand Purchase Behavior," *Journal of Marketing Research,* 10 (November), 361–375.

Iyengar, Sheena S. and Mark R. Lepper (2000), "When Choice Is Demotivating: Can One Desire Too Much of a Good Thing?" *Journal of Personality and Social Psychology,* 79 (6), 995–1006.

Jacoby, Jacob, Donald E. Speller, and Carol A. Kohn (1974a), "Brand Choice Behavior as a Function of Information Load," *Journal of Marketing Research,* 11 (February), 63–69.

——— (1974b), "Brand Choice Behavior as a Function of Information Load—Replication and Extension," *Journal of Consumer Research,* 1 (June), 33–41.

Jarvenpaa, Sirkka L. (1989), "The Effect of Task Demands and Graphical Format on Information Processing Strategies," *Management Science,* 35 (March), 285–303.

Johnson, Eric J. and John W. Payne (1985), "Effort and Accuracy in Choice," *Management Science,* 31 (April), 395–414.

Kahn, Barbara E. (1995), "Consumer Variety-Seeking among Goods and Services: An Integrative Review," *Journal of Retailing and Consumer Services,* 2 (3), 139–148.

Keller, Kevin Lane and Richard Staelin (1987), "Effects of Quality and Quantity of Information on Decision Effectiveness," *Journal of Consumer Research,* 14 (September), 200–213.

Malhotra, Naresh K. (1982), "Information Load and Consumer Decision Making," *Journal of Consumer Research,* 8 (March), 419–430.

Malhotra, Naresh K., Arun K. Jain, and Stephen W. Lagakos (1982), "The Information Overload Controversy: An Alternative Viewpoint," *Journal of Marketing,* 46 (Spring), 27–37.

Meyer, Robert J. and Eric J. Johnson (1989), "Information Overload and the Nonrobustness of Linear Models: A Comment on Keller and Staelin; Assessing Biases in Measuring Decision Effectivness and Information Overload," *Journal of Consumer Research,* 15 (March), 498–508.

Mick, David Glen (2003), "Appreciation, Advice, and Some Aspirations for Consumer Research," *Journal of Consumer Research,* 29 (March): iii–x.

Payne, John W. (1976), "Task Complexity and Contingent Processing in Decision Making: An Information Search and Protocol Analysis," *Organizational Behavior and Human Performance,* 16 (August), 366–387.

Payne, John W., James R. Bettman, and Eric J. Johnson (1988), "Adaptive Strategy Selection in Decision Making," *Journal of Experimental Psychology: Learning, Memory, and Cognition,* 14 (July), 534–552.

——— (1993), *The Adaptive Decision Maker,* New York: Cambridge University Press.

Russo, J. Edward and Barbara A. Dosher (1983), "Strategies for Multiattribute Binary Choice," *Journal of Experimental Psychology: Learning, Memory, and Cognition,* 9 (4), 676–696.

Scammon, Debra L. (1977), "Information Load and Consumers," *Journal of Consumer Research,* 4 (December), 148–155.

Shannon, Claude Elwood (1949), "The Mathematical Theory of Communication," in *The Mathematical Theory of Communication,* ed. Claude Elwood Shannon and Warren Weaver, Urbana: University of Illinois Press, 29–125.

Van Wallendael, Lori R. and Yvonne Guignard (1992), "Diagnosticity, Confidence, and the Need for Information," *Journal of Behavioral Decision Making,* 5 (1), 25–37.

West, Patricia M. (1996), "Predicting Preferences: An Examination of Agent Learning," *Journal of Consumer Research,* 23 (June), 68–80.

Wilkie, William L. (1974), "Analysis of Effects of Information Load," *Journal of Marketing Research,* 11 (November), 462–466.

Winer, Benjamin J., Donald R. Brown, and Kenneth M. Michels (1991), *Statistical Principles in Experimental Design,* 3d ed., New York: McGraw-Hill.

Wright, Peter (1975), "Consumer Choice Strategies—Simplifying vs. Optimizing," *Journal of Marketing Research,* 12 (February), 60–67.