(16)

Learning Patterns, Decision Approach, and Value of Information

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This paper reports on research designed to provide insights into the relationships between different information structures, decision approaches of decision makers and learning patterns. The motivation for the study arose from the work done previously by Mock [16].

This section of this paper summarizes the research findings from [16], and develops a motivation for investigating the additional decision-information variables. Some research findings regarding these variables are then summarized, followed by a discussion of the results of this study.

The Information Structure Experiments

A set of controlled laboratory experiments were conducted in 1968 with the objective of generating empirical evidence as to the relation between information, information value, and decision. In these experiments, businessmen and student subjects reached a set of micro-economic business decisions for 15 decision periods.

During each period, information about the problem was presented to the subjects according to two different information structures. Information structure 1 (I_1) communicated real time information about the decision environment whereas a second information structure (I_2) presented lagged information reflective of the previous period. The underlying decision

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model, though complex, could be optimized, so that within the context of the model, normative analysis would be possible.[1] Briefly, the following results were generated:

(1) The empirical value of more timely information was significantly greater than the expected theoretical value calculated according to the principles of information economics, given a one-period decision horizon. This result held for the decision-maker's ability both to minimize costs and to maximize profits.
(2) Behavioral factors seemed to contribute to this difference.
(3) For the decision model used, the more simple of the theoretical profit maximizing decision rules were empirically supported.
(4) Both satisficing and optimizing behavior was observed.
(5) Learning was evident in early decisions.

Data supporting these inferences were presented [16], but other interesting avenues of inquiry were not developed. For instance, in their discussions of the experiments, both Jensen [7] and Uretsky [22] were concerned with the role of learning in the sequential decision setting and with the individual differences that each decision-maker brought to the experiment. Individual decision-maker differences would include the approach that each manager utilized in his decision process.

In terms of learning, Uretsky [22, p. 165] commented: "How was the rate of learning influenced by perceived performance and payoffs? Was the rate of learning different under the two different information structures? Did the rate of learning vary between groups with different backgrounds or orientation?"

With respect to the two underlying information structures I_1 and I_2, Jensen [7, p. 178] commented, "Also, it would have been interesting to see the data on how long I_1 and I_2 individuals spent playing the game." Presumably Jensen is alluding to the possibility that different learning patterns would be reflected in the decision times of each group of decision-makers.

Since pilot studies had indicated the potential significance of some of the factors such as those suggested by Jensen and Uretsky, relevant data on these were collected during the original experiment. This paper reports on the findings regarding decision approach, information structure, and learning.

Learning, Decision Approach, and Information Structure Effects

At this point, it is useful to discuss some previous research that has concerned itself with these topics and to develop more concise definitions. As

[1] A mathematical description of the underlying decision model is given in Appendix A. The reader should consult [16] for further details and in particular the methods used to calculate optional decisions and used to estimate the expected and observed value of more timely information.

a point of reference, consider Table 1. The factors in the decision-information process stressed here are decision approach (heuristic versus analytic approaches) and information structure. These variables will be evaluated in terms of their effects upon average decision performance and upon changes in performance over time (learning). As the following discussions indicate, differences in decision approach and in available information can be expected to result in differences in performance and in rates of changes of performance.

DECISION APPROACH

To predict the impact of information on decision-making and to design an efficient information system, assumptions must be made as to the approach the manager takes in reaching a decision. A major problem in developing a theory of human problem solving is that there are different effects resulting from similar informational input streams due to what might be termed "structural variables" in the mental organization of the decision-maker.

> "Structural variables" provide a metric for the way a person combines information perceived from the outside world as well as internally generated information for adaptive purposes . . . like a program or set of rules which combines these items of information in specific ways. . . . For example, two persons may reach the same conclusion in a situation . . . but if the conclusion or judgment was reached by different thought processes . . . then very different adaptive consequences would be expected to follow. [18, p. 4]

This dimension of problem solving has been the subject of a number of recent studies [6, 7, 14, 15, 18, 21]. In general, the concept we called the decision approach is referred to in these studies as cognitive or management

TABLE 1

Main Variables to Be Considered

	Explanatory variables / Performance measure	Cost-benefit			Learning	
		Profit π	Input c	Decision time T	Change in decision time per period $\Delta T/t$	Change in relative profits per period $\Delta\pi/t$
Decision approach	Heuristic (H)	—	—	—	—	—
	Analytic (A)	—	—	—	—	—
Information structure	Real time (I_1)	•	•	—	—	•
	Lagged (I_2)	•	•	—	—	•

• Indicates a relationship discussed in [16].
— indicates a relationship discussed in this paper.

style. Specific definitions of these terms may vary. However, common to all of these studies is the recognition that the same information is processed differently by different decision-makers and that this difference in information processing affects the decision outcomes or actions taken.

One of the most common or persistent categories of cognitive style revolves around those decision-makers who use formal, rational analysis and take studied action versus those decision-makers who use ad hoc or trial and error analysis and spontaneous action. For example, Mathes [13] dichotomizes people into (1) *D*—people who are managerial or action people and who base their primary analysis on differences or changes in the situation and (2) *S*—people who are scientific or thinking people and form their judgments on the similarities they find in comparing situations or objects. Similarly, McKenney [14] spreads individuals along his "appraisal axis" as tending toward being either systematic (those individuals who explicitly develop plans to acquire and process their information) or intuitive (who are unaware of the concepts on which they rely or care little how they develop an information processing plan). However, McKenney states:

> Most individuals would seem to have the capacity to analyze situations in all modes of behavior. However, past processes, training and individual tendencies would indicate that most individuals have a propensity or habit of analyzing tasks for which they have a normal professional role, in one mode or the other. . . . [14, p. 13]

In other words, people who characteristically or spontaneously use an intuitive approach to problems are also capable of being systematic.

In this paper, we adopt a dichotomous classification of decision-makers based on the terms and meanings used by Huysmans [6]. Huysmans classifies operations research-like decision-makers as analytics who reduce problem situations to a core set of underlying causal relationships and base their decisions on a rational analysis of an explicit, often quantitative, model of the problem situation. In contrast, heuristics or managerial types, operate via common sense, intuition, and unquantified feelings of future developments and consider the totality of the situation as an organic whole rather than as built up from clearly identifiable parts.

Thus the heuristic (*H*) decision approach is characterized by trial and error, ad hoc sensitivity analysis, muddling-through [8], and satisficing behavior [10]. In contrast, an analytic (*A*) approach emphasizes model building, mathematical analysis, and optimization. According to profiles evident in the questionnaire responses (see Appendix C), 21 subjects were classified as heuristics, 19 as analytics, and 25 were indeterminable. Unless a profile was clearly of one class, the subject was considered indeterminable.

INFORMATION STRUCTURE

An information structure can be defined as a specified set of rules which determine data collection, measurement, processing, and transmission. Alternative information structures can be compared by varying these rules to produce differences in the timing, degree of detail, or format of a com-

munication. From the standpoint of information systems design, differences in information structures are of interest only if they are expected to affect decisions or to result in differential costs. A common way of viewing the possible impact of various messages is in terms of the decision-maker's uncertainty regarding the probable occurrences of states of the world.[2] If different information structures lead to different degrees of uncertainty about states of the world that are relevant, the value of such information differences are worthy of study. Thus a part of the analysis in this paper focuses on the relationship between information structure and decision time. If an information structure leads to less decision uncertainty, then possibly economies in decision time exist under that information system.

LEARNING

In the two previous sections, differences in information and in decision approach were regarded as explanatory (causal) variables in a decision-making situation (such as a business game). However the effects of differences in information and decision approach do not remain static over time. Rather they change as the decision-maker adapts to the information stream and the situation it describes. Such an adaptive process is called learning. Basically, there are two types of definitions of learning—factual and theoretical definitions:

> As regards the factual definitions, there has always been general agreement among authorities on the subject that learning refers to a more or less permanent change in behavior which occurs as a result of practice. . . . Another, different, idea which occurs quite frequently in theoretical definitions of learning treats the phenomenon as one closely related to perception and defines it in terms of a reorganization of the perceptual, psychological, or behavioral world of the learner. . . . [13]

Although a theoretical definition of learning might be more useful in understanding the effects of cognitive style on decision, its measurement was not possible with the data generated during the experiment. Therefore, a factual definition was chosen which measures learning operationally in terms of changes (improvements) in performance, as indicated in Table 1. More specifically, learning will refer to changes in choice behavior, being measured both by changes in the length of time a subject takes to make a choice, and by increases in profits or decreases in costs associated with his decision choice (*ceteris paribus*).

Hypotheses, Experimental Setting, and Controls

HYPOTHESES

As discussed earlier, the relationships between decision time,[3] decision approach, information structure, value of information, and learning are of

[2] For example, Marschak [12], Feltham [5], Feltham and Demski [4].

[3] Decision time is defined to be the time interval between each period's decision implementation. (Feedback was immediate.)

TABLE 2

Summary of Hypotheses

Explanatory variables	Main hypotheses	
Decision approach: Heuristic (H) Analytic (A)	1. Decision payoff differences (profit = π and input cost = c)	H_1: $\bar{\pi}(A) - \bar{\pi}(H) > 0$ H_2: $\bar{c}(A) - \bar{c}(H) < 0$
	2. Decision time (T)	H_3: $\bar{T}(A) - \bar{T}(H) > 0$ (initially) H_4: $\bar{T}(A) - \bar{T}(H) < 0$ (subsequently)
	3. Learning patterns (changes, Δ, in π and T)	H_5: $\Delta[\bar{\pi}(A)/\pi^*(I)] = \Delta[\bar{\pi}(H)/\pi^*(I)]$ H_6: $\Delta\bar{T}(A) > \Delta\bar{T}(H)$ (initially)
Information structure: Real time (I_1) Lagged (I_2)	1. Decision payoff differences	H_7: $\bar{\pi}(I_1) - \bar{\pi}(I_2) > 0$ H_8: $\bar{c}(I_1) - \bar{c}(I_2) < 0$
	2. Decision time differences	H_9: $\bar{T}(I_1) - \bar{T}(I_2) < 0$
	3. Learning patterns	H_{10}: $\Delta[\bar{\pi}(I_1)/\pi^*(I_1)] = \Delta[\bar{\pi}(I_2)/\pi^*(I_2)]$ H_{11}: $\Delta\bar{T}(I_1) = \Delta\bar{T}(I_2)$ (initially)

* = optimal values.

$^-$ = average values.

Thus for each subject class K: $\bar{c}(K)$ = average input costs, $\bar{T}(K)$ = average decision time, $\bar{\pi}(K)$ = average profits, $\pi^*(K)$ = optimal profits, $\bar{\pi}(K) \div \pi^*(K)$ = relative profits earned, I_j = information structure j.

main concern. Table 2 includes a summary of the hypotheses and develops the notation for subsequent discussion. Each set of related hypotheses is discussed in turn.

H_1 and H_2: Payoff Differences Related to Decision Approach. The first hypotheses essentially imply that decision-makers classified as analytics will outperform decision-makers who rely upon heuristic decision strategies both in terms of profits (H_1) and input cost (H_2). The main reasons supporting such hypotheses stem from the very nature of the decision problem which in essence could be structured as an analytical model that could be mathematically optimized. The analytical approach can be expected to be more effective for such a problem. Some readers of the previous research paper [16] felt that the model may have been testing analytical skill of decision-makers and that this may have had a biasing effect upon results attributed to differences in information structure. The effect of these variables is therefore of interest and is considered in this paper.

H_3 and H_4: Decision Time Differences Related to Decision Approach. Hypotheses 3 and 4 imply that (per period) average decision time for analytics is expected to exceed that of heuristics in the initial decision periods and vice versa for later decision periods. The rationale underlying these propositions is tied to the basic ways in which analytics and heuristics are perceived to approach decisions. The analytic approach incorporates to a

greater degree search, model determination, model analysis (optimization), and the incorporation of feedback and historical data into these processes. Faced with a new problem, we would expect such analyses initially to be quite time-consuming, especially when compared with a heuristic approach which incorporates trial and error and relies upon feedback as to the effectiveness of alternative decision strategies. By his very nature, a heuristic is expected to learn from action rather than analysis. Given the analytical nature of the decision problem, we would expect these relationships to reverse in later periods as analytics realize relatively greater economies in decision times (H_4).

H_5 and H_6: Rates of Learning Related to Decision Approach. Although learning patterns can be expected in most sequential decision experiments, we have no reason to believe that rates of learning, measured in terms of performance change (relative performance improvement from one period to the next), can be expected to be significantly different between heuristics and analytics.

$$H_5 : \Delta[\bar{\pi}(A)/\pi^*(I)] = \Delta[\bar{\pi}(II)/\pi^*(I)]$$

where

$\bar{\pi}(\ )/\pi^*$ = ratio of actual profits and optimal profits

Δ = change from one period to the next

$\pi^*(I)$ = optimal attainable profits under the appropriate information structure.

Observe that the ratio of attained profits over optimal profits possible is taken to measure performance. The main reason for the utilization of this ratio is that the cyclical nature of the economic parameters of the model influenced the level of obtainable profits. Standardizing the attained profits by optimal profits eliminates these cyclical factors.

However, if learning is measured in terms of efficiencies in decision time it follows that: (H_6) in initial periods rates of change in decision time of analytics will exceed that of heuristics.[4] This, of course, is consistent with H_3 and H_4 and their arguments.

H_7 and H_8: Value of Information Structure. These hypotheses are derived from the expected value of the more timely information available under I_1. As shown in [16], the evidence supports these hypotheses and indeed supports the contention that the value of information was significantly greater than theoretically predicted. As these questions were discussed in detail in [16], they will not be considered any further here except to the extent that the results of this paper affect previous inferences.

H_9, H_{10} and H_{11}: Decision Time Differences and Learning Related to Information Structure. As pointed out earlier, differences in information can be expected to affect decision time. Specifically, under conditions of less uncertainty provided by real time information, average decision time

[4] For decision times, learning rates are negative; thus only in absolute value terms can this hypothesis be expected to hold.

is postulated to be less than under situations of greater uncertainty (I_2).[5] This is the essence of H_9, which points to two types of efficiencies that can be expected under information structure I_1: profit performance and decision time.

Consistent with the arguments in the discussions of H_6, H_{10} indicates that although performance efficiencies are expected under I_1, there is no a priori reason to expect differences in learning rates as measured by changes in relative profit performance. Thus H_{10} predicts a constant profit learning rate for subjects classified in terms of I_1 and I_2.

H_{11} considers learning in terms of incremental decision times and hypothesizes that decision-makers with more timely information (I_1) will *not* exhibit significantly different learning rates than subjects operating with I_2 information, although there is some reason to expect that I_2 learning rates will exceed those of I_1 subjects.

EXPERIMENTAL SETTING AND CONTROLS

The data collected to test the above hypotheses were obtained in a set of business game experiments described in detail in [16] and summarized here. These experiments are high in terms of internal validity (control) so that any inferences apply strictly to decision and information differences in a particular business game.

The experiment was taken by 25 businessmen and 47 students who were asked to reach business-type decisions concerning production input quantities, advertising levels, and total production quantities for 15 decision periods. The experimental controls can be summarized as follows

> Briefly, each subject, after receiving a set of written instructions, was placed in a soundproof cubicle. The cubicle contained pencil and paper for simple calculations and a teletype. The teletype was the main communication and control device through which the subject input decisions and through which all information and feedback was communicated to him. The data collected in post-mortem questionnaires and through observation confirms the success of the control design, especially in terms of the motivation provided by monetary payoffs and the interest and challenge inherent in the decision problem. [16, p. 127]

In this environment, decisions were mainly dependent upon a set of exogenous price and demand factors which were communicated to the subject with differing degrees of uncertainty depending on the information structure. Feedback was communicated in the form of accounting financial statements.

Statistical Tests and Results

The sample population can be partitioned according to information structure and decision approach.[6] The sample is shown in Table 3 accord-

[5] This hypothesis is not valid in general, but in this decision environment uncertainty necessitates the development of predictions which can be expected to require decision time.

[6] See Appendix C.

TABLE 3
Sample Sizes

	Information system 1	Information system 2	Totals
Analytic decision-makers	12	7	19
Heuristic decision-makers	11	10	21
Other decision-makers	14	11	25
Totals	37	28	65

ing to subject size. The observations consisted of 15 decisions and their results for each subject.

The tests used parametric normal statistics, and their validity depends upon whether the assumptions underlying this class of statistics hold. An attempt has been made to consider such specification problems and they are discussed where appropriate.[7] Most of the hypotheses and their tests concern differences among average behavior. Thus, while sample sizes tend to be small, the Central Limit Theorem still applies. Also, descriptive statistical analysis of the underlying data did not contradict basic normality assumptions.

A summary of hypothesis tests is given in Table 4. Statistical tests on the null hypothesis of no significant difference have been constructed where rejection of the null hypothesis usually indicates evidence for the acceptance of our main hypothesis. Each class of hypotheses will be discussed according to (1) profit or cost performance differences, (2) decision time differences, or (3) differences in learning rates measured in terms of profits and decision times. Basic figures depict the essential relationships tested. Supporting tables are presented in Appendix B.

PROFIT AND COST PERFORMANCE FOR ANALYTICS AND HEURISTICS (H_1 AND H_2)

Given the nature of the decision problem underlying the experiments, analytic decision-makers can be expected to outperform heuristics both in terms of profits attained and input costs incurred. In Figure 1 differences

[7] Of particular concern in time series data is correlation of the data over time, heteroscedasticity, and normality.

TABLE 4

Summary of Hypothesis Tests

Main hypotheses	Decision periods considered	t or F statistics under null hypothesis	Null hypothesis rejected or accepted	Main hypothesis supported or not supported
H_1: Analytics can be expected to outperform heuristics in terms of profits	4–15	$t = 1.95$	Rejected ($\alpha = .025$)	H_1 supported
H_2: Analytics can be expected to outperform heuristics in terms of input cost minimization	4–15	$t = -4.26$	Rejected ($\alpha = .025$)	H_2 supported
H_3: Initially, analytics are expected to require additional decision time	2–8	$t = 1.86$	Rejected ($\alpha = .05$)	H_3 supported
H_4: During latter periods, analytics are expected to require less decision time	9–15	$t = .31$	Accepted	H_4 not supported
H_5: Rates of learning measured in terms of profit improvement are not expected to differ between analytics and heuristics	4–15	$F = 1.8$ (analytics) $F = .006$ (heuristics)	Regressions were not significant. Therefore no learning was evident.	H_5 supported
H_6: Rate of learning measured in terms of economics in decision time are initially expected to be larger for analytics	2–9	$F = -.0031$	Accepted	H_6 not supported
H_7: I_1 subjects are expected to require less decision time	2–15	$t = 1.89$	Rejected ($\alpha = .025$)	H_7 not supported
H_{10}: No significant learning differences are expected between I_1 and I_2 subjects when learning is measured in terms of changes in profits.	4–15	$F = .08$ (I_1) $F = .008$ (I_2)	Regressions were not significant. Therefore no learning was evident.	H_{10} supported
H_{11}: No significant learning differences are expected between I_1 and I_2 subjects when learning is measured in terms of rate of decrease in decision time	2–9	$F = -.0014$	Accepted	H_{11} supported

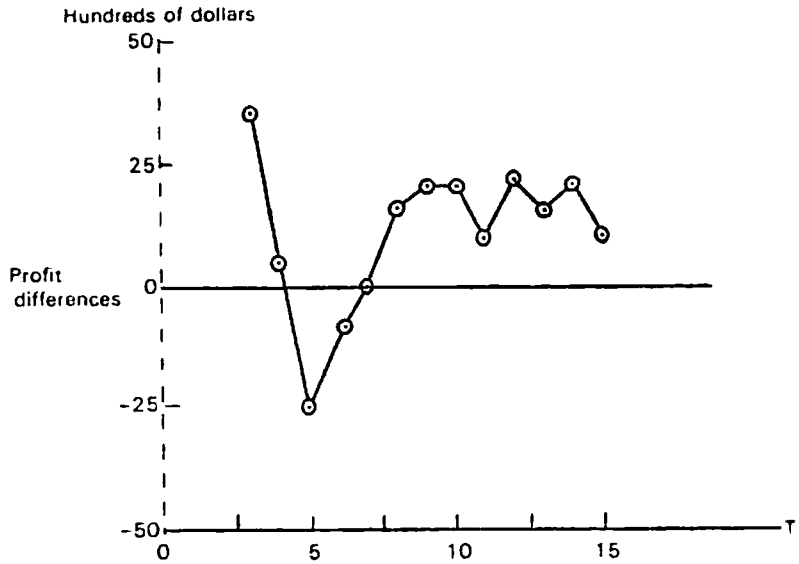

FIG. 1. Differences in Average Profits Attained for Analytics and Heuristics (*A* and *H*, Hypothesis 1)

in average profits ($\bar{\pi}(A) - \bar{\pi}(H)$) have been plotted. Support for H_1 is evident since for each period except 5 and 6 the difference is nonnegative.

A *t*-test of the differences permits us to reject the assumption that they were insignificant at the .025 level. This test also supports H_1.[8]

In Figure 2, differences in the input costs incurred are plotted ($\bar{c}(A) - \bar{c}(H)$). Except for period 3, average input costs of heuristic decision-makers exceeded that of analytics. A *t*-test also indicated that these differences are significantly different from zero, thus supporting H_2.[9]

From the standpoint of information system design and decision theory, evidence indicating possible significance of decision approach raises several questions for future exploration. For instance, are there alternative feedback schemes that are more appropriate for each class of decision-maker? How does decision approach affect the expected value of changes in the information systems?[10]

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[8] These tests excluded the initial three periods where pilot studies had indicated that significant learning would occur and thus initial differential learning rates could not affect these tests.

[9] The hypotheses H_1 and H_2 are related but are not identical. Profit maximization (H_1) was a considerably more difficult decision problem than cost minimization (H_2). Thus while we would expect consistency between H_1 and H_2, it is not necessary.

[10] The intergroup characteristics of these data are being investigated. In [16], significant differences in cost and profit performance between I_1 and I_2 decision-makers were observed.

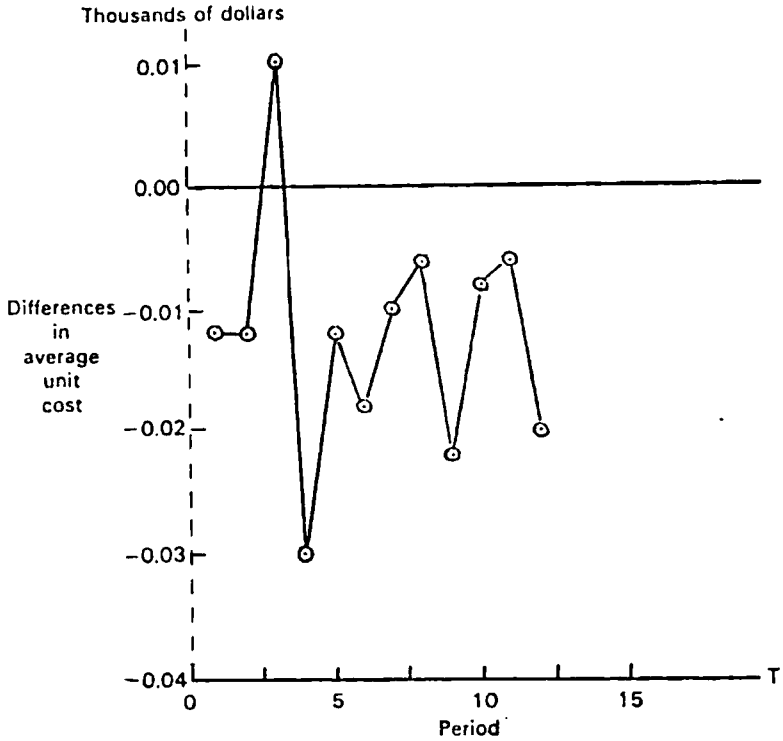

FIG. 2. Differences in Average Costs Between Analytics and Heuristics (Hypothesis 2)

INTERGROUP DIFFERENCES IN TIME TAKEN TO REACH DECISIONS (H_3, H_4, H_9)

As was argued earlier, problem analysis, and thus decision time, can be expected to vary among subject groups. When considering decision approach, analytics were predicted to utilize more decision time than heuristics in the initial periods (H_3), and vice versa for later or subsequent periods (H_4). As a rule-of-thumb, split halves were taken, so initial applied to periods 2–8 and subsequent to periods 9–15.[11] The differences in decision times (A and H) are plotted in Figure 3. This Figure shows that analytics did indeed utilize more time in periods 2 through 8, whereas in the later periods the total difference seems small. The t-tests on these differences indicated they were significant in the case of H_3, but not for H_4.

From the Figures, observe that results would not be affected by changing the split by one period in either direction. Also, the variation of the differences (measured in absolute minutes) is clearly less in the later time span. This is a result of learning which will be discussed later. When considered jointly with the inferences on H_1 and H_2, these results show that

[11] Accurate decision times for period 1 were not available.

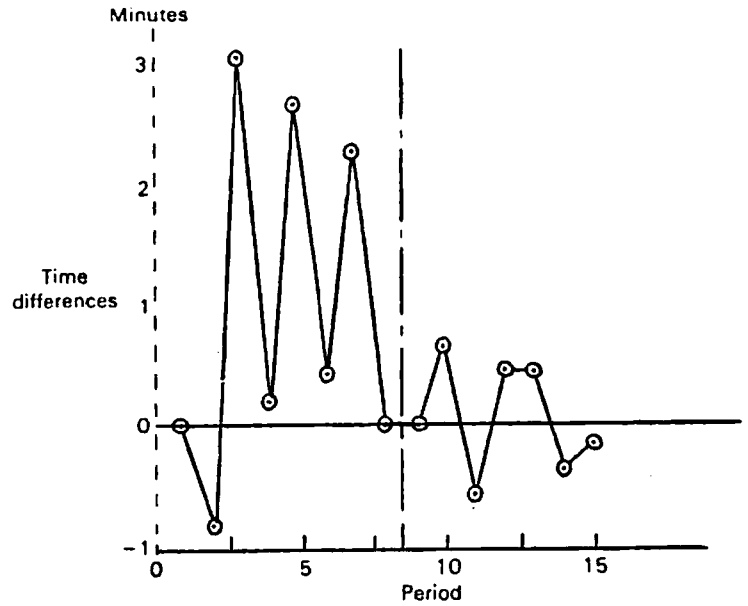

FIG. 3. Plot of the Differences in the Decision Times Between Analytics and Heuristics for Each Period (Hypotheses 3 and 4)

analytics performed better in terms of payoffs, but at a cost of higher decision times. This would suggest the need for a joint measure of performance, say profits minus decision time, but a satisfactory trade-off measure was not found.

Decision times were also related to the information structure available to the decision-maker. In Figure 4, differences $(\bar{T}(I_1) - \bar{T}(I_2))$ in these times are plotted for I_1 and I_2 subjects.

H_9 predicts that decisions reached under information structure I_1 could be expected to be made more rapidly than those reached under I_2. Therefore these differences are expected to be negative. However, the data in Figure 4 show that these differences tended to be positive. Indeed, a t-test shows them to be significantly different from zero in the positive direction. Thus H_9 is rejected. This result tends to increase the uncertainty as to the cause for the superior performance observed of I_1 subjects in [16]. The data show again that I_1 participants received more valuable information, but required a longer decision period.

DIFFERENCES IN LEARNING MEASURED IN RATES OF CHANGE IN RELATIVE PROFIT PERFORMANCE (H_5 AND H_{10})

The measure of learning was based on changes in performance over time, where performance is measured first in terms of profits (H_5 and H_{10}) and then by decision times (H_6 and H_{11}). These differences are plotted in Figures 5 and 6. Relative profits are percentages of actual profits to optimal

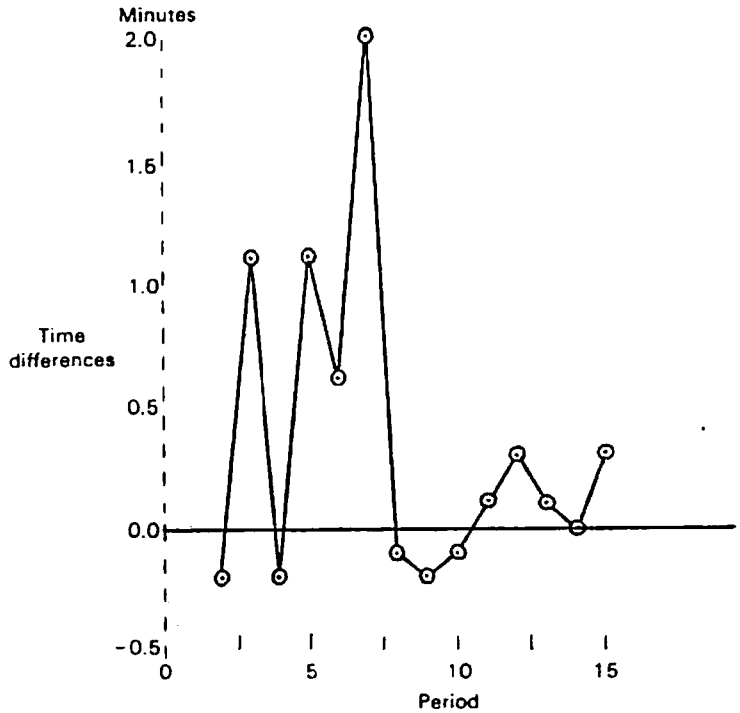

FIG. 4. Plot of the Differences in Average Decision Times Between Subjects Operating under I_1 and I_2 Information for Each Period

profits achievable,[12] and are used to neutralize any cyclical effects of the market.

Periods 1, 2 and 3 in the experiments were set aside as learning periods with the subjects receiving a message to this fact at the end of period 3. If learning curves were linear, then differences in rates of learning would result in differences in the slopes of the learning curves. Clearly, learning did occur in the initial three periods with little subsequent change in relative profits in the following 12 periods. In fact, the slope (β coefficients) of the regression lines plotted for periods 4–15 are nearly horizontal as they ranged from .8 to −.03 but were all statistically insignificant. These data tend to support H_8 and H_{10} in that no learning was observed for either partition of subjects.[13] Although the information differences in these experiments did not result in different learning rates, information structures differing in feedback characteristics may be expected to lead to learning differences.[14]

[12] See [16].

[13] Attempts to transform these data for periods 1–15 logarithmically or exponentially into (approximately) linear forms were not successful, so the observed patterns did not fit the traditional forms.

[14] The value of information in learning is discussed in Mock [17]. Information

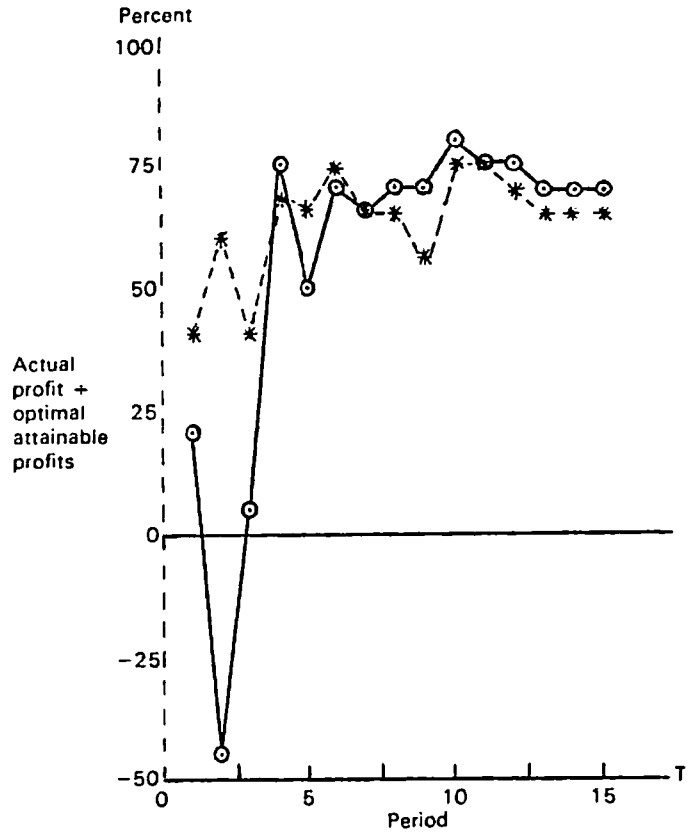

FIG. 5. Plot by Decision Period of: Average Relative Profits for Analytics (0) Average Relative Profits for Heuristics (•)

LEARNING DIFFERENCES MEASURED IN RATE OF CHANGE IN DECISION TIME (H_6 AND H_{11}).

Recall that, learning rates in terms of decision time taken should be greater (though negative) initially for analytics versus heuristics and for I_1 and I_2 subjects.

The average decision times are plotted in Figures 7–10 both in terms of minutes and their logarithms. A clear learning pattern is evident in each chart, with the pattern made more linear by the logarithmic transformation.

Using linear regression analysis, rates of learning (slopes) were estimated for the initial split-half periods. The results are shown in Table 5. The F statistics indicate that the coefficients were not significantly different for periods 2 through 9 for both subject groups. This is confirmed in Figures 7–10 where the appropriate regression lines have been plotted for

value in this sense entails assisting the decision-maker in the identification of effective strategies and of valid decision models and assumptions.

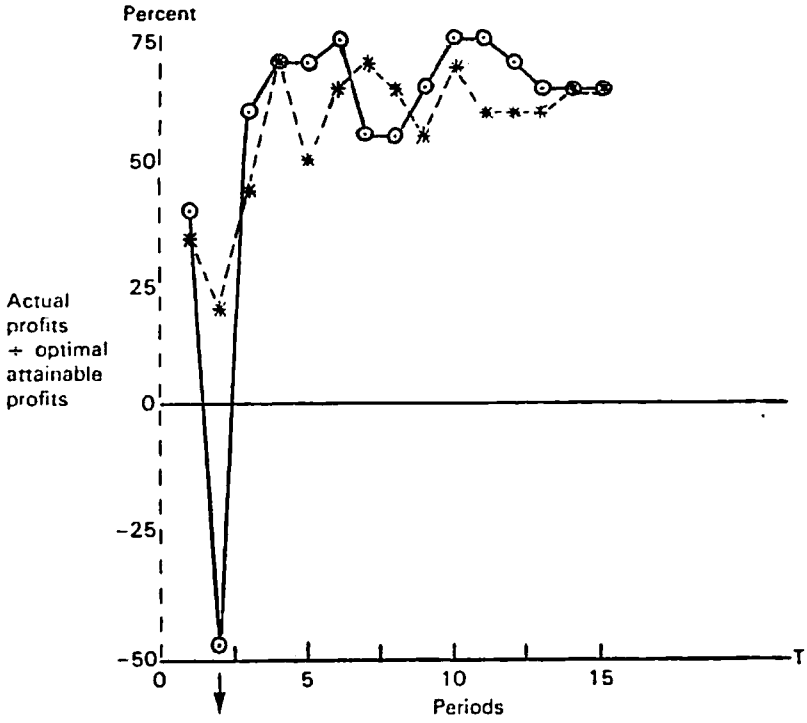

FIG. 6. Plot for Periods 1–15 of: Average Relative Profits for Information Structure I_1 (0); Average Relative Profits for Information Structure I_2 (•)

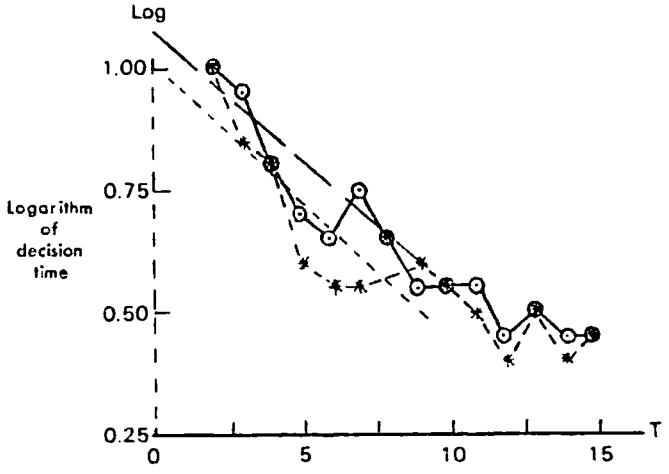

FIG. 7. (1) Plot of Logarithm of Decision Times Utilized by Analytics (0) and Heuristics (•) Including Linear Regression Lines to Estimate Learning Rate; (2) Plot of Average Actual Decision Times Utilized

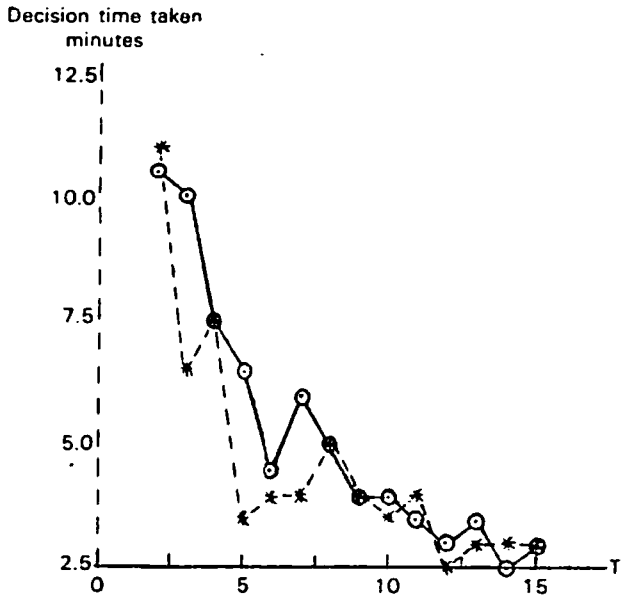

FIG. 8. Plot of Average Decision Times of Heuristics (•)

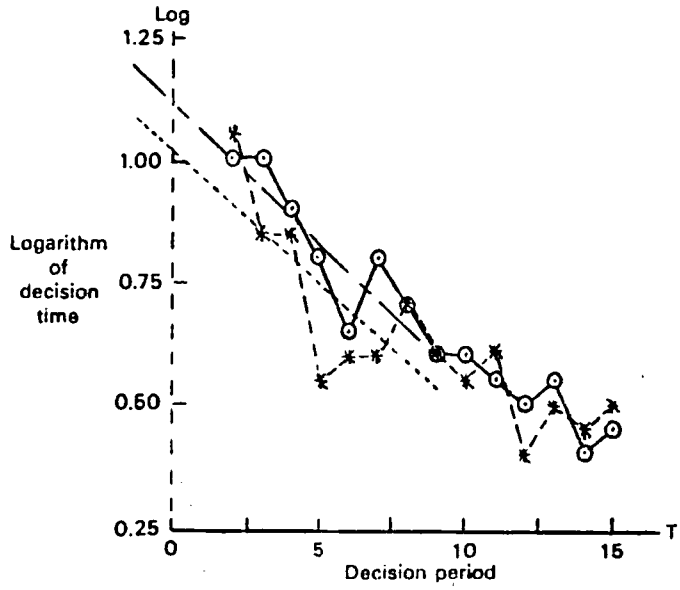

FIG. 9. (1) Plot of Logarithm of Decision Times Utilized by I_1 (0) and I_3 (•) Subjects and Linear Regression Lines to Estimate Learning Rates of Periods 2-9; (2) Plot of Average Actual Decision Times Utilized

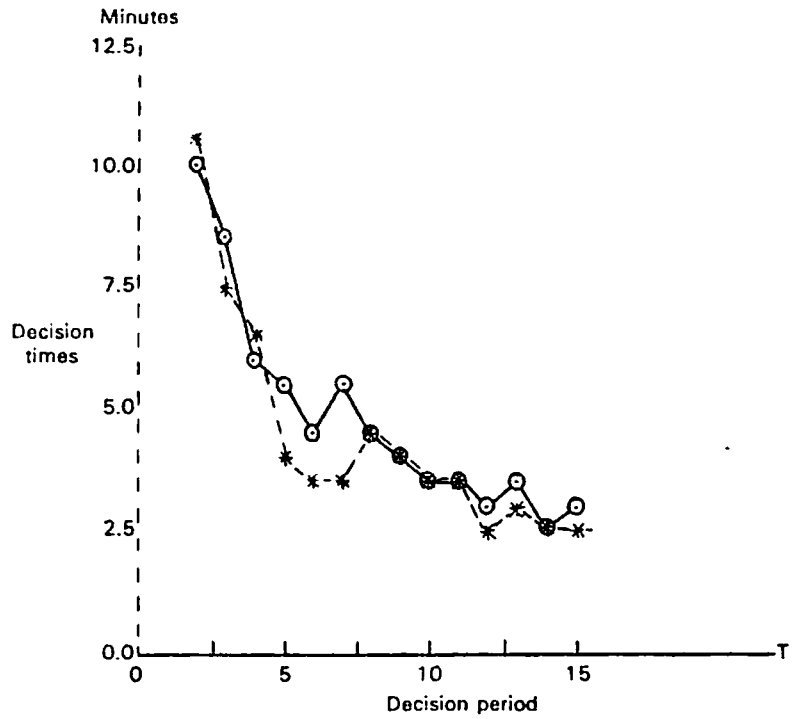

FIG. 10. Plot of Average Decision Times Taken by I_1 (0) and I_2 (•) Subjects

the initial periods. In both cases, the slopes of the regression lines are nearly identical with only the intercepts differing. In the case of Figures 7 and 8, the difference in intercepts confirms the earlier conclusion that analytics initially utilized more decision time (H_3).

Since the data indicated that I_1 and I_2 subjects did not differ in time or profit rates of learning, learning effects did not seem to bias the value of information results discussed in [16].

Summary

This research was undertaken to investigate the effect of decision approach and information structure upon decision performance and learning. The results reported indicate that decision approach had a significant effect

TABLE 5

Rates of Learning for the Initial Split-Half Periods

Decision class	Learning rate (β coefficient)	F statistic for the null hypothesis $\beta_i = \beta_j$
Analytics	−.05596	−.0031
Heuristics	−.05364	
I_1	−.05653	−.0014
I_2	−.05818	

upon payoffs and decision times. If decision approach is an important information system design variable, further research is needed to develop a taxonomy of relevant decision-maker characteristics which can be used to design more individualized information systems. Clearly, the capabilities of modern computer-based accounting systems make such systems feasible.

In contrast, learning patterns did not depend upon decision approach. Measured by profit performance, learning was not observed in the final 13 decision periods. When measured by decision times, the logarithmic learning curves were not significantly different.

In studying the effect of information structures upon learning patterns, no learning effect was found in the case of profit performance, and equivalent rates of learning were observed in the case of observed decision times. Yet, subjects who received real-time information (I_1) utilized significantly longer decision times than those receiving lagged information. This particular observation lends some uncertainty as to the cause of the superior performance of I_1 subjects reported in [16].

APPENDIX A

The underlying decision model for the experiments:
Maximize:

$$\pi_t = P_t Q_t - C_t$$

subject to

$$P_t = \beta_t - .03\,Q_t + 95\,A_t - A_t^2 \tag{1}$$

$$C_t = \alpha_t + c_t\,(.0075\,Q_t^2 - .075\,Q_t) + 5000\,A_t \tag{2}$$

$$1 = 2\,(M_t L_t)^{1/2} \tag{3}$$

$$c_t = p_{1t} M_t + p_{2t} L_t \tag{4}$$

$$M_t, L_t > 0 \tag{5}$$

$$Q_t \geq 10 \tag{6}$$

$$0 \leq A < 75 \tag{7}$$

α_t, β_t, p_{1t}, and P_{2t} fixed for each t and greater than 0;
where for each period t:

π_t = profit
P_t = selling price
Q_t = quantity produced and sold*
C_t = total cost
A_t = advertising units purchased*
M_t = material input*

* decision variables

L_t = labor input
c_t = input cost per standard unit produced
p_{1t} = cost of materials
p_{2t} = cost of labor.

The constraints (5), (6), (7) and (8) were not clearly evident in a draft of [16], and Jensen [5] pointed out that an infinite number of solutions would lead to infinite profits. For instance, if one could produce negative amounts of product, costs (equation (2)) become revenues. This is, of course, a correct mathematical interpretation but an unlikely economic situation. Under the constrained model, such solutions are infeasible, and unique optimal decisions do exist.

APPENDIX B

TABLE B1

Average Profit per Period (in $000's) Attained by Each Subject Group and Their Intergroup Differences

Period	Information structure I_1	Information structure I_2	Analytics A	Heuristics H	Group difference I_1 and I_2	Group difference A and H
1	60.737	51.624	32.104	56.266	9.113	24.162
2	−279.752	28.86	−676.77	89.694	−308.612	−766.464
3	100.863	73.507	102.26	66.684	27.356	35.576
4	145.534	143.771	147.987	140.506	1.763	7.481
5	159.779	115.517	117.425	144.599	44.262	−27.174
6	177.607	150.001	163.147	174.339	27.606	−11.192
7	120.892	143.935	133.777	135.068	−23.043	−1.291
8	112.156	139.838	147.964	132.443	−27.682	15.521
9	116.036	101.359	122.037	100.613	14.677	21.424
10	189.072	178.467	202.846	184.971	10.605	17.875
11	224.262	186.593	233.501	221.325	37.669	12.176
12	246.165	213.304	263.698	242.807	32.861	20.891
13	171.862	159.742	186.658	171.128	12.12	15.53
14	196.641	192.458	213.54	195.60	4.183	17.94
15	199.739	193.914	210.78	200.95	5.825	9.83
Aver. profits per period 4-15	170.43	159.91	178.64	170.36	10.52	8.34
Standard deviation	42.18	33.76	46.93	41.29	22.97	14.69
Standard error	12.18	9.75	13.55	11.92	6.63	4.24

TABLE B2

Average Unit Cost per Period (in $000's)

Period	Information structure I_1	Information structure I_3	Analytics A	Heuristics H	Group differences between I_1 and I_3	Group differences between A and H
1	1.0435	1.0531	1.1027	1.0241	−.0096	.0786
2	1.2168	1.044	1.056	1.0709	.1728	−.0149
3	1.0101	1.0131	0.9957	1.0154	.003	−.0197
4	.8992	.8854	.8846	.8961	.0138	−.0115
5	.9018	.9077	.8903	.9023	−.0059	−.012
6	.8005	.834	.8081	.799	−.0335	.0091
7	.8345	.8541	.8173	.8479	−.0196	−.0306
8	.8786	.8844	.8716	.8828	.0058	−.0112
9	.8727	.8797	.8624	.8804	−.007	−.018
10	.781	.803	.7785	.7879	−.022	−.0094
11	.7012	.7386	.6967	.7028	−.0374	.0061
12	.6446	.692	.6313	.6539	−.0474	−.0226
13	.6879	.6851	.6683	.6763	.0028	−.008
14	.5996	.6237	.5996	.6063	.0099	−.0067
15	.653	.6716	.6412	.6617	.0186	.0205
Aver. unit cost/ period 3–15	.795	.803	.788	.791	−.008	−.010
Standard deviation	.116	.115	.140	.128	.028	.014

TABLE B3

Average Decision Times Taken (Minutes)

Period	Information structure I_1	Information structure I_3	Analytics A	Heuristics H	Difference between I_1 and I_3	Difference between A and H
1						
2	10.14	10.36	10.26	11.14	−.22	−0.88
3	8.49	7.43	9.79	6.71	1.06	3.08
4	6.13	6.32	7.53	7.33	−.19	.20
5	5.27	4.14	6.32	3.62	1.13	2.70
6	4.30	3.71	4.53	4.19	.58	.34
7	5.40	3.36	6.00	3.86	2.04	2.14
8	4.30	4.43	4.79	4.81	−.13	−0.02
9	3.76	4.00	4.21	4.14	−.24	.07
10	3.40	3.50	4.05	3.38	−.10	.67
11	3.40	3.32	3.42	3.95	.08	−0.53
12	2.84	2.57	3.05	2.62	.27	.43
13	3.30	3.21	3.53	3.62	.09	0.36
14	2.68	2.64	2.53	2.90	.04	−0.37
15	2.95	2.68	2.89	3.14	.27	−0.25
Overall aver. decision time	4.74	4.41	5.21	4.67	.342	.239
Standard deviation	2.218	2.201	2.480	2.293	.664	.966
Standard error	.593	.588	.663	.613	.177	.258

TABLE B4

Average Relative Profit per Period (Average Profits as a Percentage of Optimal Profits per Period)

Period	Information structure I_1	Information structure I_2	Analytics *A*	Heuristics *H*	Optimal profits	
					I_1	I_2
1	41.5%	35.3%	006.8%	24.3%	$146,279	$146,244
2	−187.7	19.4	−135.6	29.8	149,026	149,003
3	60.5	44.1	17.5	07.3	166,695	166,695
4	72.2	71.3	51.8	36.4	204,102	201,636
5	69.6	50.4	50.2	34.8	229,461	229,301
6	74.9	64.0	69.0	73.9	237,119	234,260
7	56.6	67.8	62.8	63.4	213,661	212,415
8	53.8	67.2	71.0	63.6	208,328	208,063
9	64.8	56.6	68.2	56.2	179,113	178,974
10	74.9	72.3	81.0	74.1	252,329	246,907
11	73.4	62.2	76.9	73.1	305,518	300,083
12	70.0	60.9	75.1	69.2	351,448	350,006
13	63.6	59.5	69.2	63.6	270,056	268,305
14	59.8	63.9	70.4	64.6	304,562	301,353
15	66.6	64.9	70.4	67.1	299,706	298,973

APPENDIX C

Classification of Subjects as Analytics and Heuristics

In accordance with the notions of analytic and heuristic decision types discussed in the text of this paper, subjects were classified according to their questionnaire responses. If subjects did not fall clearly into either category, they were classified as indeterminable. The most relevant question and abstracts of subject responses follow. Other question responses were used to validate the classification.

How did you go about reaching the various decisions for this experiment?

Classification (*A* or *H*)	I.D. No.	Response
H	25	Using relationship of past data and formula, demand, etc.
H	26	Developed a trend input. Key to the decision was demand index and the unit material cost compared to total production cost.
H	28	Trial and error.
H	93	Trying to see the relationships of various input combinations to output results. Varying different factors at different times depending on known data.
A	98	Tried to analyze the model—solution form seemed to work, solution for advertising did not work so I experimented. I was about to experiment with quantity when the game was over.
A	121	First I analyzed the three basic formulas and attempted to determine how to optimize each. Then, based on the data, I tried to find the optimum advertising, quantity and material used per unit.
A	123	Mostly by analyzing the equations given to find the maximizing (in the case of sales) or minimizing (in the case of costs)

Classification (*A* or *H*)	I.D. No.	Response
		relationships. The one time I took a big gamble just to see what would happen was the one period I showed a loss.
H	125	Decisions made in relation to the previous period. Watched which way the variables were going and decided accordingly.
H	126	Mostly trying to get a feel for how it reacted—watching relationship of material and labor cost plus demand in relation to prior results.
A	127	At first I studied relationships in formula form.
H	128	Based on past history.
A	129	By working out the problems mathematically as best as possible, and also by trying to determine certain basic relationships.
H	141	I mostly relied on the new information in relation to the old.
H	145	Mainly experimenting. Realized that advertising was a factor in the sales to be completed; tried analyzing the material based on quantity.
H	146	Interpretation of Exhibit II and thinking positively in terms of sales volume being responsive to advertising.
H	148	I used past history and the previous period's results.
H	32	I struggled for the first couple of periods, but then made adjustments on previous period's figures and tried again.
H	35	An approximation method—previous results plus demand change.
A	37	Max: $(D - .03Q + 95A - A^2)Q - C(7.5Q^2 - 75Q/1000) -$ fixed cost $- 5{,}000A$.
H	42	Experimentation—when I found a formula which produced relatively good results I stuck with it with minor variations depending on demand index.
A	45	M and A analyzed. Q was by guess and estimates of which direction to go from past performance.
A	48	Devised minimum cost mathematically; estimated next period's costs by watching current trends.
H	55	Correlating the results of cost and sales dollar with the decision variables.
A	56	Evaluation of past performance, evaluation of demand indicator of the economy and minimum of input costs.
H	59	Reviewing the previous data; judging from the formula, main focus was placed on D, CM, CL. Did not compute the formula on each occasion.
A	64	Took partial derivatives of expressions for profit with regard to A, Q, and M. Developed from these. Worked out Q-A relation and then saw the M depended only on CM and CL and worked from there.
A	65	At first I just made decisions fairly similar to the previous periods. After a few decisions began to work the math relationships between demand and price and Q between M and L.
A	66	After working out a few relationships between quantity, profit and costs, I decided on important areas to be high and low, then went on previous information.
H	67	I sought for the dependence of the variables and their sensitivity.

Classification (*A* or *H*)	I.D. No.	Response
H	73	For *A* I tried a marketing method until I reached the point when I felt that the range of 37-39 units was most effective for most demands—modified if demand was very high or low. For *Q* I used trial and error experiments with demand index. For *M* I used the relationship of cost of each and formula on the *L* and *M* relationship.
A	74	For *M*—used $2C/2M = 0$. For *A*—used $2P/2A$ where $P = (95A - A^2)$, plus adjustment. For *Q*—experience plus adjustment of the change in demand.
A	79	Algebraic manipulation to get feel of objective function.
H	81	Continuing to tabulate figures as on Exhibit II. Making approximate extrapolations and estimates based on previous performance.
H	86	I would like to think quantitatively; however, after reading the instructions and making some basic calculations (i.e., attempts to determine the relationships between *D* and *P*, *M* and *L*, etc.) subsequent decisions were based on intuition and the historical evidence.
H	87	Trial and error.
A	89	Minimum input cost. Varied output with fixed cost and demand level—varied advertising accordingly.
A	96	*A* based on *D*. *M* and *L* based on *CM* and *CL*. *Q* based on *D*, *CM* and *CL*.
A	97	Attempted to minimize total costs by watching production expenses and estimating a conservative *A* policy based on demand index.
H	102	At first it was mere guessing. Then I noticed a relationship between units, *M* and *A* and I tried to keep these three numbers pretty much the same way. If fixed costs went up, I decreased *A* and increased *QA*.
H	104	By studying the example given. First time I just picked the numbers, but later on, I increased or decreased according to fixed cost and demand index.
H	108	At first I made a survey of Exhibit II. I paid most attention to years 4-6, since the company made most profits during these three years. I got an idea that my advertising units were better between 35-38. Then according to the information of next period's expenses I got from the computer, I made my decision.
A	115	I tried to determine (a) the relationship between *A* and sales; (b) the relationship between volume and cost; and (c) the minimum cost input mix.
A	117	Compared relationship *CM* to *CL*. Optimum advertising units —40.

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