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ABSTRACT

Assessing the economic impacts of alternative Information System (IS) designs and selecting IS design parameter values for a given decision setting are two important research issues in the domain of Information Systems. Evaluation studies based on information economics provide rigorous but restricted models, while traditional MIS studies suggest richer but less formal evaluation frameworks. In this paper, we attempt to combine the analytical rigor and descriptive richness into a unified and consistent basis for evaluating IS designs and making design modifications (improvements) to existing IS. Expanding on the concepts of information economics, a multi-dimensional mathematical model of information quality is developed. Several properties of the quality model with implications for system design are derived in the form of propositions. The impacts of information quality differential upon the effectiveness of an operational level decision setting are investigated through a decision-theoretic approach. Next, a hierarchical model is suggested for relating system design variables to the quality of information generated by the IS. Based on the quality differential impact analysis and the hierarchical model, a structured methodology for making design changes to existing IS is outlined.

1. INTRODUCTION

Two distinct but related issues in the domain of Information Systems (IS) are system design and evaluation. What are the criteria on which alternative IS designs should be evaluated? How should the design parameters of an IS be determined for a given context of use? These have remained two key research questions in the field for many years. A review of the relevant literature reveals two categories of research, based on information economics (Feltham 1968; Hilton 1981; Marschak 1963, 1971; Marschak and Radner 1972; Merkhofer 1977) and traditional MIS approaches such as the user satisfaction method (Bailey and Pearson 1983; Epstein and King 1982; Nolan and Seward 1974; Zmud 1978). Information economics provides a rigorous methodology for evaluating "information structures" in terms of a single criterion called "fineness" (Marschak and Radner 1972). The MIS literature, although not mathematically as precise as information economics, suggests numerous information attributes or criteria that are not considered by the information economics models. Clearly, there exists a gap between the rigor of information economics models and the richness of the MIS studies.

In this paper, we attempt to develop a unified and theoretically sound basis for the evaluation and design of IS used in operational level decision making. One of the goals of this research is to preserve both the analytical precision of the quantitative models and the realistic features of the MIS approach. Expanding on the concept of "information structures," we develop a mathematical model of information quality. The economic impacts of the information quality differential on the decisions utilizing the information are determined. Some properties of the information quality model with implications for the system designer are derived. For example, we show how less detailed[1] information (which is cheaper to obtain) can lead to the same payoff for a class of decision problems. Counter-intuitive results, such as reduced payoffs with increased reporting frequency, and the conditions under which such problems are circumvented are obtained. We also provide an exposition of the design tradeoffs in the choice of information attribute values. Building on the impacts analysis, we propose a structured methodology for making design improvements to existing systems. As a typical example of an operational level decision setting, we use a production scheduling scenario as the reference context.

2. MOTIVATION AND PRIOR RESEARCH

Many IS evaluation techniques employ user satisfaction as a surrogate measure of system effectiveness (Bailey and Pearson 1983; Ives, Olson and Baroudi 1983; Nolan and Seward 1974; Powers and Dickson 1973). While this approach measures the users' satisfaction with an IS, assessing the economic impacts of the IS is beyond the scope of this method (Chismar, Kriebel and Melone 1985).

In information economics, there has been rigorous research on the "value of information" using an information attribute called "fineness" (Marschak and Radner 1972). The "fineness" criterion provides a formal mechanism for comparing "information structures." An "information structure" is an abstraction of an IS and may be characterized by a single "likelihood function." However, as indicated by MIS studies (Adams 1975; Davis 1974; Emery 1971; Epstein and King 1982; Powers and Dickson 1973; Zmud 1978), an IS requires a multidimensional description, a feature not considered by the information economics models.

Thus, it is evident that in spite of the existence of a body of literature, there is no generalized analytical model of information quality and value. As emphasized by Kriebel (1979), a consistent mathematical model of information quality is the first step in the evaluation of an IS. The crux of the evaluation problem lies in being able to measure the impact of information quality differential upon the payoff to the decision maker (DM) utilizing the information. In this paper, one of our goals is to reduce the large information attribute set found in the literature into a parsimonious but sufficient set of analytically precise definitions. This precision eliminates redundant attributes, helps derive propositions with system design implications, and provides a method for calculating the dollar impacts of information quality on the DM's decisions. Moreover, the proposed analysis can be used to make design improvements to existing systems.

In Section 3, we present a conceptual model for the separation of system and decision characteristics. We define a sufficient but parsimonious set of signal attributes in Section 4 and outline a decision-theoretic method for evaluating the impacts of information quality upon the DM's payoffs in Section 5. We discuss "subsystem characteristics," design parameters and their general functional relationships to signal attributes in Section 6. In Section 7, we provide a structured framework for choosing and setting values of design parameters through "dominance analysis."

3. SEPARATION OF SIGNAL, SYSTEM AND DECISION CHARACTERISTICS

Evaluation of IS design involves consideration of two components: the IS itself and the DM's environment. The IS designer determines the setting of design variables such as the number of information processors, storage capacity and number of error detection mechanisms. The choice of these variables, in turn, determines the attributes of information (signals) generated by the IS. The impacts of these attributes on the DM's effectiveness depend on the characteristics of the decision setting. In order that the same set of definitions may be applied to any context, the definitions of design variables and signal attributes must be independent of the decision setting. A conceptual model for this separation of the IS and decision characteristics is shown in Figure 1.

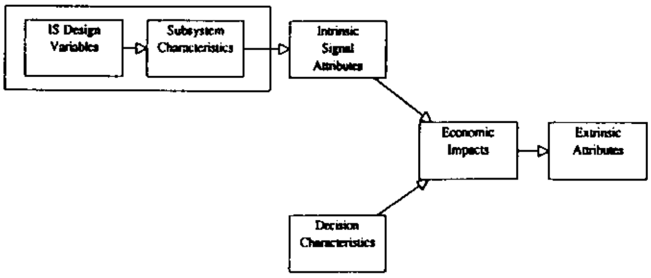

Figure 1. A Conceptual Model for IS Design Analysis: Separation of Signal, System, and Decision Characteristics

The signals generated by an IS have a set of attributes, which can be defined to be independent of any decision context, and may therefore be called *intrinsic attributes*. The design variables are linked to the intrinsic attributes via an intermediate level of variables, the *subsystem characteristics*. In Section 7, the IS is represented as a collection of subsystems. Each subsystem has certain characteristics such as sampling and information updating time, processing accuracy, etc. (henceforth referred to as subsystem characteristics), which are determined by the design variables for that subsystem. The intuitive justification for this three-level hierarchy consisting of design variables, subsystem characteristics, and signal attributes is as follows. Typically, there are a large number of design variables for an IS. Dealing with these design variables directly makes design modification a difficult task. The intermediate level (subsystem characteristics) enables the designer to perform "dominance analysis" and thereby identify a small number of "dominant" design variables. Together with the characteristics of the decision context, the signal attributes determine the DM's payoff (or cost). Marschak and Radner (1972) analyzed the impacts of "fineness" of information structures on a DM's payoff. In this paper, the analysis is extended to incorporate multiple dimensions of information quality and their impacts on the DM's expected payoff.

Extrinsic attributes are payoff-relevant (P-R) descriptions of intrinsic attributes.[2] They indicate whether differences in signal attributes are relevant for a given decision setting. For example, two systems may differ in terms of their accuracy and still yield the same payoff under certain conditions. Extrinsic attributes are thus measured by the impact of signal attribute differentials upon a particular decision context. Intrinsic attributes are stated in technological terms such as time, frequency, and probability of error, while extrinsic attributes are stated in units of payoff (e.g., dollars). The designer of the system deals with intrinsic attributes, while the economic impacts (extrinsic attributes) are of interest to the DM.

4. INTRINSIC ATTRIBUTES

In this section, we build on the MIS evaluation literature and define a mathematically consistent set of intrinsic signal attributes. While we do not claim this set to constitute an exhaustive list, we show that it captures the essence of a large number of attributes found in the literature. We propose the following attribute set.

1. Signal timing
2. Reporting frequency
3. Monitoring time (period)
4. Signal resolution
5. Intrinsic accuracy
6. Intrinsic informativeness

These attributes are generally not independent of each other. This non-orthogonality gives rise to interesting tradeoffs between the attributes, an issue discussed in Section 7 on design choices.

Before defining the attributes, it is important to provide a black-box description of an IS. An IS reports on several sources of uncertainty (e.g., demand, inventory, lead times, raw material prices). A state of the world may be defined as a vector of random variables associated with uncertainty sources and is described by a set of signals, $\{y\}$, from the IS. For every IS there is a set of states, $\{s\} = S$, that are recognized by the IS as being distinct. For example, one IS may report the exact lead time, while another may only recognize short and long lead time ranges. Generally, the signals are not perfect, being contaminated with "noise." This noise is expressed in the form of a likelihood function[3] $\lambda(y|s)$, the probability of receiving $y \in Y$, given that $s \in S$ has occurred (see Marschak and Radner 1972).

4.1 Signal Timing and Reporting Frequency

Definition 1: Timing of a signal is the time at which the signal is received by a DM. The reporting frequency, f, is the inverse of the time interval between the receipt of two successive signals by a DM.

While it may seem natural to associate reporting frequency with repetitive decision making, in Section 6, we show how reporting frequency can be important for a single-decision setting.

4.2 Monitoring Time (Period)

Definition 2: Let an IS monitor the states of uncertainty sources 1,..., N at times $t_1,...,t_N$ respectively. The set of these times is called the monitoring time of the IS. If the monitoring of an uncertainty source, i, takes place from t_i to t_i', then the interval $[t_i, t_i']$ is used to denote the monitoring period for i.

The attributes, "reporting delay," "age of information," and "currency of information," can be derived from monitoring time. "Reporting delay" and "age of information" for any uncertainty source can be found by subtracting the corresponding monitoring time element from signal timing and current time respectively. "Currency of information" is decision context dependent and can be defined as the time at which the decision is taken minus the monitoring time.

4.3 Signal Resolution

Definition 3: Let S_1 and S_2 be the sets of distinct states for IS 1 and 2 respectively. IS 1 is said to have a higher signal resolution compared to IS 2, if the following condition is satisfied:

$$\text{For all } s_1 \in S_1 \ \exists s_2 \in S_2 \text{ such that } s_1 \subseteq s_2 \qquad (1)$$

Intuitively, the condition implies that system 1 reports greater details either or both in terms of the number of uncertainty sources and the value ranges. For example, the IS2 database may contain information on demand and lead time, a subset of the information content of the IS1 database (demand, lead time and prices), and therefore have lower resolution. As a second example, system 1 may recognize every integer value of demand, while system 2 may be sensitive only to low, medium and high ranges of demand. Resolution also covers aggregation of information (such as monthly versus weekly data, or total demand versus demand for individual items).

Resolution does not consider the "noise" present in the information. For example, the system that reports demand for individual items is considered to have higher resolution than the one reporting total demand, even though the latter may have less "noise" due to a natural averaging effect. For systems that are noiseless with respect to their state partitions, resolution and "fineness" (as used by Marschak and Radner) have the same meaning.[4]

4.4 Intrinsic Accuracy

Definition 4: For two systems differing only in terms of their likelihood functions, one is called intrinsically more accurate than the other only if it is Blackwell sufficient for the other (Blackwell 1953; Hilton 1981). Let system i have a likelihood function $\lambda(y_i|s)$, $i=1,2$. $\{s\} = S$ is the set of distinct states for the two IS, and $\{y_i\} = Y_i$ is the signal set of system i. Since S and Y can be continuous or discrete sets, we use the integral sign to denote a generalized summation operator. Of course, any coarsening of S or Y is discrete. System 1 is intrinsically more accurate or Blackwell sufficient for system 2 if a stochastic transformation $g(y_1,y_2)$ exists for which the following are satisfied:

$$\lambda(y_2|s) = \int_{y_1 \in Y_1} g(y_1,y_2)\lambda(y_1|s) \quad \forall s \in S \ \forall y_2 \in Y_2 \qquad (2)$$

$$\int_{y_2 \epsilon Y_2} g(y_1,y_2) = 1 \quad \forall y_1 \epsilon Y_1 \tag{3}$$

$$0 < \int_{y_1 \epsilon Y_1} g(y_1,y_2) < \infty \quad \forall y_2 \epsilon Y_2 \tag{4}$$

More intuitively, one system is more accurate than the other if the latter can be realized from the former through a stochastic transformation. The resolutions of the two systems must be the same for a comparison of intrinsic accuracy. For example, it is meaningless to compare the accuracies of the blind men, each of whom is describing a different part of the elephant.

4.5 Intrinsic Informativeness

The definition of intrinsic informativeness is the same as that of intrinsic accuracy with the restriction on resolution removed. Note that uncertainty about the true states of the world is introduced by differences in accuracy and resolution. Thus informativeness is the net effect of these differences. The importance of informativeness is that it allows us to compare a set of IS (with comparable resolutions) without reference to a decision context. Thus if IS1 is more informative than IS2, then this relationship holds true for any setting. Therefore, conditions under which one system is more informative than another are of special interest to us.

Higher resolution does not guarantee higher informativeness. The noise present in the signals may affect informativeness significantly. Similarly, low noise alone cannot ensure high informativeness, since resolution (level of detail) is the second determinant of informativeness. The set of special cases where resolution is sufficient for informativeness is discussed below.

4.6 Intra-Partition and Inter-Partition Noise

Let $\{s\}$ and $\{\theta\}$ be partitions of a state space S and let $\{\theta\}$ have higher resolution than $\{s\}$. Let $s_i = \{\theta^1_i, \theta^2_i, \ldots, \theta^m_i\}$ for all i as shown in Figure 2. Let $\{w^j_i\}$ be the signal set corresponding to $\{\theta^j_i\}$.

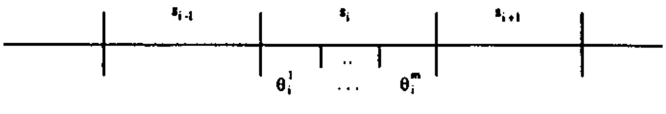

Figure 2. State Space Partitions with Comparable Resolution

Definition 5: If $\lambda(w^l_k \mid \theta^j_i) = 0$ for $i \neq k$ and any l and j, then there is no ***inter-partition*** noise with respect to $\{s\}$.

If $\lambda(w^l_i \mid \theta^j_i) \neq 0$ for $j \neq l$, then ***intra-partition*** noise exists with respect to $\{s\}$.

Proposition 1: A noisy system with higher resolution is more informative than a noiseless system (with lower resolution) if the noise is only intra-partition type.

Proof: Let $\{y\}$ be the signal set corresponding to $\{s\}$ in the above definition. Using Definition 5, it is seen that a stochastic transformation from $\{\theta\}$ to $\{s\}$, given by $g(w^l_k, y_i) = 1$ for $i=k$, and 0 otherwise, satisfies conditions 2, 3 and 4.

Discussion: This proposition shows that resolution can be the sole determinant of informativeness when the noise can be separated into disjoint components corresponding to the partition elements s_i, $i = 1,2,..,n$. It provides a simple tool for comparing the informativeness of a subset of IS without doing the complex sufficiency calculations.

4.7 Mapping between the Proposed and Existing Attribute Sets

Having defined the signal attributes, we provide a mapping between these attributes and those mentioned in the literature. This comparison highlights the confusion that exists in a section of the evaluation literature due to mixing of intrinsic and extrinsic attributes and decision characteristics. It is not possible to show a mathematical correspondence between the proposed attributes and those found in the literature because many of the latter ones have not been defined precisely.

From the table, we note that several attributes such as timeliness, relevance, and redundancy, which have been classified as information attributes, are actually decision context dependent (extrinsic attributes). While intrinsic attributes can be compared for two IS without reference to a decision context, it is not meaningful to use extrinsic attributes as dimensions of information quality.

5. EXTRINSIC ATTRIBUTES: IMPACTS OF SIGNAL ATTRIBUTES

Two systems may differ in terms of their signal attributes; however, the difference in payoff to the DM due to this attribute differential depends on the decision characteristics. Thus, two systems with different signal timings may yield the same payoff in certain situations. In that case, the two systems have the same "timeliness" (to be described as an extrinsic attribute), though the signal attributes are different. This phenomenon is central to the notion of payoff-relevance in that intrinsic attribute differences may or may not cause a difference in the DM's payoff. When they do not, the attribute differences are not relevant to the context.

CURRENT LITERATURE	PROPOSED ATTRIBUTE	COMMENTS
Frequency (Davis) Repetitiveness (Adams)	Reporting frequency	
Frequency of use (Gorry and Scott-Morton) (Gorry and Scott-Morton)	-	Decision characteristic
Response time (Emery)	Signal timing	
Timeliness (Feltham; Hilton)	Extrinsic attribute	Context dependent
Reporting delay (Epstein and King)	Signal timing - Monitoring time	
Currency (Gorry and Scott-Morton)	Decision time - Monitoring time	Context dependent
Age (Adams)	Current time - Monitoring time	
Time horizon (Gorry and Scott-Morton) Reporting cycle (Epstein and King)	Monitoring time	Time covered by the report, e.g., daily demand for a week.
Scope (Gorry and Scott-Morton) Content (Adams; Emery)	Resolution	Number of uncertainty sources included; aggregation; range of values.
Fineness (Marschak and Radner)	Resolution	IS is noiseless for the set of distinct states.
Aggregation (Gorry and Scott-Morton), Summarization (Adams)	Resolution	
Relevance (Adams), Selectivity (Emery), Redundancy (Davis)	Extrinsic attribute (Action relevant resolution)	Context dependent
Accuracy (Adams; Emery), Reliability (Davis; Emery), Precision (Adams)	Accuracy	
Flexibility (Emery; Merkhofer)	-	Decision characteristic
Cost (Davis; Powers and Dickson) Value (Davis)		Not a signal attribute

We show that differences in payoff occur due to a reduction of the DM's action set and/or uncertainty differences regarding the true states of the world. The individual and joint impacts of intrinsic attributes upon the DM's payoffs are illustrated below using a production scheduling decision context. The relevant uncertainty sources for this setting are demand, inventory, and shop floor condition (e.g., machine loading and operator capacity), one or more of which may be important for a given setting. For simplicity, we only consider demand uncertainty in this paper. Information on these uncertainty sources is generally provided by an integrated Material Requirements Planning (MRP) based IS, which contains order processing/forecasting, inventory tracking and scheduling subsystems as components. The information received from the system may be inaccurate, dated, too aggregate, delayed or irrelevant. We attempt to estimate the dollar impacts of these information attributes.

Let a be the amount to be produced, an action chosen by the DM. Let {s} denote the set of demand states. Since the MRP-based IS is rarely perfect, the correct amount to be produced is not known with certainty. Then an outcome may be defined in terms of shortage or excess, depending on the state and the action chosen. We use a simple cost function defined as $z(a,s) = c^+w^+ + c^-w^-$, where w^+ and w^- refer to the amount of excess and shortage, and c^+ and c^- to the corresponding unit cost. In the following subsections, we use the terms "expected payoff" and "expected cost" interchangeably, with the understanding that payoff in the current context is the negative of the expected cost.

5.1 Payoff Relevant Timing

IS signals often get delayed due to various reasons. For example, long batching delays in a batch-oriented system are inevitable. In this section, we assess the impact of this delay on the DM's cost.

Definition 6: Let the timings of two otherwise identical systems be t_1 and t_2. If the DM's action set gets reduced in the interval $[t_1,t_2]$, such that an action element which is optimal for some signal is lost, then the system with timing t_1 is considered more timely. The value of timeliness is the difference in the DM's expected payoff. Thus, if the action set remains stationary in $[t_1,t_2]$, then the value of timeliness is zero.

An important subset of decision problems involves the choice of numerical variables (e.g., the amount to produce or order in case of production or order schedules). In many situations, the maximum value of the variable that can be chosen decreases with time. For example, with a given deadline, the maximum amount that can be produced reduces with time. Similarly, for raw materials purchase, a vendor may fill in orders on a FCFS basis. In that case, orders placed later have a lower chance of getting filled in a given period. Let A(t) denote the maximum value of the decision variable that can be chosen at t. Also, let p(s) be the prior probability of s.

Proposition 2: With a stationary likelihood function, earlier signal timing is preferred if

$$\frac{\partial A}{\partial t} < 0.$$

Proof: The difference in expected costs due to signal timings t_1 and t_2 can be shown to be

$$\sum_{k=1}^{2} (-1)^{k+1} \int_{y \epsilon Y} \min_{a \epsilon [0,A(t_k)]} \int_{s \epsilon S} z(a,s)\lambda(s|y)p(y) \tag{5}$$

where $\lambda(s|y) = \lambda(y|s)p(s) / p(y)$ and the marginal probability

$$p(y) = \int_{s \epsilon S} \lambda(y|s)p(s)$$

Since $A(t_1) > A(t_2)$ for $t_2 > t_1$, if $a > A(t_2)$ for any signal y, then expression (5) is less than zero, showing that the expected cost is lower for system 1.

Discussion: This proposition provides a way to measure the usefulness of a system on the basis of its signal timing. The proposition implicitly indicates the possibility of a noiseless system becoming inferior to a null system because of the former's signal timing. A numerical example involving demand uncertainty follows.

Example: Let there be two demand states $s_1 = 10$ and $s_2 = 20$ with prior probabilities $p_1 = p_2 = .5$. Let the maximum amount that can be produced be time variant and be given by

$$A(t) = \begin{cases} 30\text{-}3t & \text{if } t \leq 10 \\ 0 & \text{if } t > 10 \end{cases}$$

Let the DM's cost function be $z = 10(a\text{-}s)^2$ and the demand information system likelihood matrix be $\lambda(y_1|s_1)$, $\lambda(y_2|s_1)$, $\lambda(y_1|s_2)$, $\lambda(y_2|s_2)$ = .6, .4, .4, .6 respectively.

Before t = 4, A(t) does not become binding on the optimal amounts to produce, and the total minimum cost is \$240. Thus earlier signal timing has no impact before t = 4. But for t = 5 and 6, the expected cost increases to \$245 and \$340 respectively. In fact, it is not worth having the system (even if for free) with signal timing $t \geq 6$, since the DM's expected cost with a null system is \$250.

5.2 Payoff Relevant Accuracy

Definition 7: For two systems differing only in terms of their intrinsic accuracies, the value of payoff relevant (P-R) accuracy is the difference in expected payoffs (or costs) given by expression (5) above, with λ_k representing the likelihood function of system k, k = 1,2 and with $t_1 = t_2$.

From the definition of intrinsic accuracy, it can be noted that the payoff associated with a more accurate system is at least as high as that from a less accurate system.

5.3 Payoff Relevant Reporting Frequency

Reporting frequency, f, depends on the type of system in use. An on-line system displays information immediately, while a batch system reports only periodically. A deferred on-line system has a reporting frequency in between those of on-line and batch systems. For a single decision in a given time frame [0,T] reporting frequency impacts become subtle and can be thought of as a combination of accuracy and timing effects.

Say a production decision has to be taken by T. If $1/f < T$, then the DM receives more than one signal (describing the state of the same uncertainty sources, though with increasing accuracy) in [0,T], assuming that the first signal is received at t=0. When accuracy increases with time (due to a reduction in uncertainty over time), the n^{th} signal is always more accurate than the $n\text{-}1^{th}$ signal for n = 1,2,...,n. However, if the maximum amount that can be produced, A(t), decreases over time, then the DM has to determine the optimal trade off between "good" actions and more accurate information. In particular, after receiving a signal, the DM has to choose whether it is optimal to take an action immediately (denoted by α) or to wait for the next signal (denoted by β). If the i^{th} signal received at time (i-1)/f is y, let it be denoted by y_i. The DM's expected cost with a reporting frequency f is given by:

$$\int_{y_1 \epsilon Y} \min_{\delta \epsilon [\alpha,\beta]} \xi_1 p(y_1) \quad \text{where } \xi_1 \tag{6}$$

$$= \min_{a \epsilon [0, A(0)]} \int_{s \epsilon S} z(a,s)\lambda(s|y_1) \quad \text{if } \delta = \alpha$$

$$= \int_{y_2 \epsilon Y} \min_{\delta \epsilon [\alpha,\beta]} \xi_2 p(y_2|y_1) \quad \text{if } \delta = \beta$$

ξ_2 may similarly be defined terms of ξ_3.

Proposition 3: For two otherwise identical systems 1 and 2 with reporting frequencies f_1 and f_2 respectively, $f_1 > f_2$ does not guarantee lower expected cost with system 1.

Proof: By construction. Say f_1 and f_2 are such that three signals (at $t=0$, $1/f_1$, and $2/f_1$) from system 1 and two signals (at $t=0$, $1/f_2$) from system 2 are received by the DM in the interval $[0,T]$. Since the accuracy increases with time, signal 2 (from system 1) $<_a$ signal 2 (from system 2) $<_a$ signal 3 (from system 1), where $<_a$ stands for "less accurate than." Let y_{ij} denote the j^{th} signal from system i, $i=1,2$. The first signal is denoted by y_1 for both systems. Say A(t) and the likelihood function are such that for all y_1, $\delta = \beta$, and that

$$\int_{y_{22} \epsilon Y} \min_{a \epsilon [0, A(1/f_2)]} \int_{s \epsilon S} z(a,s)\lambda(s|y_{22})p(y_{22}|y_1) <$$

$$\int_{y_{12} \epsilon Y} \min_{a \epsilon [0, A(1/f_1)]} \int_{s \epsilon S} z(a,s)\lambda(s|y_{12})p(y_{12}|y_1) <$$

$$\int_{y_{13} \epsilon Y} \min_{a \epsilon [0, A(2/f_1)]} \int_{s \epsilon S} z(a,s)\lambda(s|y_{13})p(y_{13}|y_1)$$

The above condition implies that for all signals at 0, the DM waits for a later signal, and that the expected cost of taking an action at $t=1/f_2$ is lower than those of taking actions at either $1/f_1$ or $2/f_1$.

Discussion: This proposition shows that an increase in reporting frequency can lead to an increase in expected cost if the action set is time variant. The design implication that emerges as a corollary is that the reporting frequency should always be increased by an integer multiple of the original frequency. Otherwise, arbitrary increases in frequency (as used in the proof above) can lead to higher costs. A numerical example follows.

Example: Let two otherwise identical demand forecasting IS 1 and 2 report demand at intervals of 3 and 4 weeks respectively. If the signal accuracy increases with time, the likelihood matrix of each IS gradually approaches an identity matrix. For illustration, let the time variation be given by $\lambda_t(y_1|s_1) = \lambda_t(y_2|s_2) = 1 - .4e^{-t/8}$. Let A(t) be given by $36-t^2$ if $t \leq 6$, and 0 otherwise. Let the cost function be $z = 10(a-s)^2$.

With system 1, the DM is forced to take an action at $t=3$, because the next signal is at $t=6$ with $A(6) = 0$. With system 2 (which has lower reporting frequency), the DM takes an action after receiving the second signal at $t = 4$, and this results in the lowest expected cost.

5.4 Payoff Relevant Monitoring Time

Very often a DM may need to know the value of a random variable (e.g., demand) at a particular time in order to make a decision. For example, a DM using a simple forecasting routine needs to know the demand, inventory and shop floor conditions for day t in order to make a production decision for day t+1. In this case, t is the P-R monitoring time. If the IS monitors the value of the random variables at any other point in time, then the corresponding signal becomes less valuable, even though it may be perfect for the state of the world at the sampling instant. In general, the larger the difference between the P-R and actual monitoring times, the less the P-R relevance of the signal. In fact, when the difference is sufficiently high, the signal has no relevance to the state of the world at the required time. Let s_i^t denote state s_i at time t. If the monitoring time is 0 and the P-R time is t, then the expected cost is given by

$$\int_{y \epsilon Y} \min_{a \epsilon [0,A]} \int_{s^0 \epsilon S} \int_{s^t \epsilon S} z(a,s_i^t)p(s_i^t|s_j^0)\, \lambda(s_j^0|y)p(y) \tag{7}$$

where $p(s_i^t|s_j^0)$ is the probability of state s_i occurring at t, given that state s_j occurred at 0.

Proposition 4: Let the functional form for the conditional probability $p(s_i^t|s_j^o)$ be given by

$= e^{\alpha t} + (1 - e^{\alpha t})\, p(s_i^t)$ if $i=j$

$= p(s_i^t)[1 - e^{-\alpha t}]$ otherwise.

For sufficiently large t, the system approaches a null system. The rate of approach increases with α.

Proof: Let $p(s^t)$ be the DM's prior probability density on $\{s\}$ at t. Then as $t \to \infty$, $p(s^t_i|s^0_j) \to p(s^\infty_i)$

Therefore, $\forall\alpha\forall\epsilon > 0\ \exists t$ such that $|p(s^t_i) - p(s^t_i|s^0_j)| < \epsilon\ \forall$ i and j. Thus, for sufficiently small ϵ, i.e., for sufficiently large t, expression (7) tends to

$$\int_{y\epsilon Y} \min_{a\epsilon[0,A]} \int_{s^0\epsilon S} \int_{s^t\epsilon S} z(a,s^t_i)p(s^t_i)\lambda(s^0_j|y)p(y)$$

$$= \min_{a\epsilon[0,A]} \int_{s^t\epsilon S} z(a,s^t)p(s^t)$$

which is simply the expected cost for a null system. With larger values of α and for a given value of ϵ, t becomes smaller and the system approaches the null system faster.

Discussion: The functional form of the conditional probability is fairly general in that, as t increases, the information on the state at time 0 becomes progressively irrelevant in predicting the state at t. α is a measure of the rate at which the relevance of the signal is lost. For example, if the demand for a product is highly variable, then the corresponding α has a small value, indicating that the relevance of the information is lost quickly. This proposition indicates that it is desirable that the actual monitoring time be close to the P-R time. Unfortunately, this may not always be feasible when long information processing times and time variant action sets are involved. In those cases, the monitoring may have to be done earlier to avoid a loss of timeliness of the signal. This concept is further discussed with an example in Section 7 on design modifications.

5.5 Resolution Adequacy

Definition 8: Let S_p denote the payoff-relevant set of the states for a DM. Let Θ be the set of states considered as distinct by an IS. The resolution of the IS is just adequate if $\Theta = S_p$, lower or higher than adequate accordingly as Θ has lower or higher resolution than S_p.

5.5.1 Cost of Lower-Than-Adequate Resolution

Let $\{\theta\} = \Theta$ have lower resolution than the P-R set $\{s_p\}$. To determine the impacts of this resolution on the DM's payoff, we calculate the conditional probability $\lambda(s_p|y)$ from $\lambda(\Theta|y)$, as

$$\lambda(s_p|y) = \sum_{\theta\epsilon\Theta} p(s_p|\theta)\lambda(\theta|y) \text{ where}$$

$$p(s_p|\theta) = p(\theta|s_p)p(s_p) \Big/ \int_{s_p\epsilon S_p} p(\theta|s_p)p(s_p) \text{ and}$$

$\forall s_p \varepsilon S_p\ \exists\theta\varepsilon\Theta$ such that $p(\theta|s_p) = 1$.

The expected cost is given by

$$\int_{y\epsilon Y} \min_{a\epsilon[0,A]} \int_{s_p\epsilon S_p} z(a,s_p)\lambda(s_p|y)p(y)$$

Example: A numerical example involving aggregation of information may be useful. Consider the demand for two items 1 and 2 denoted by random variables x_1 and x_2 respectively. Let $x_1, x_2\ \varepsilon\ \{100, 200\}$. Let the cost function be given by $z(a_1,a_2,x_1,x_2) = 4(a_1-x_1) + 6(a_2-x_2)^2$. Thus, there are four P-R states. Let an $(x_1,x_2) = (100, 100), (100, 200), (200, 100), (200,200)$. Let an order processing system aggregate the information by reporting the total demand. The set of distinct states of this IS is given by $\{\theta\} = \{200, 300, 400\}$. Let the prior density on the states be uniform. Also, let the system be noiseless with respect to $\{\theta\}$. With the system, the expected cost is found to be \$12,500 with $a^*_1 = a^*_2 = 150$. This is the (opportunity) cost of lower-than-adequate resolution, since the cost with a perfect system and just-adequate resolution is \$0 in this example.

5.5.2 Cost of Higher-Than-Adequate Resolution

If Θ has higher resolution than S_p, then some additional effort is required upon the receipt of a signal in order to find the corresponding state in the P-R set S_p. In this case, the difference in cost is equal to the difference in the cost of additional information processing.

5.5.3 Action Relevant Resolution

For a wide variety of decision problems, the level of detail required is coarser than the corresponding P-R levels. For example, consider a production system with two batch sizes: 50 and 80 units. Say demand can take four values, 30, 50, 80 and 100 units. The P-R partition of the demand space has four corresponding elements. However, note that the restricted optimal batch sizes are 50 units for any one of the states 30 and 50 and 80 units for the states 80 and 100 (assuming that the unit shortage cost is equal to the unit excess cost). Therefore, for this restricted action set, an IS that cannot distinguish between the states 30 and 50, and between 80 and 100 results in the same expected cost as the one providing the P-R partition. We refer to the less detailed IS as having the action-relevant (A-R) resolution. This exposition is both interesting and important because it shows the possibility of getting the same payoff (or cost) with less detailed information for a class of decision problems.

Definition 9: Let $\{s_a\} = S_a$ be the state space partition of an IS. This IS is said to have action relevant resolution, if, for every s_a, only one action is optimal for every state that may be contained in s_a.

Proposition 5: Consider two IS, one with the A-R resolution and the other with higher resolution. Let the systems be noiseless with respect to their own state partitions. The expected payoff (or cost) difference between the two IS is zero.

Proof: Referring to Figure 2, consider $\{s\}$ and $\{\theta\}$ as partitions with A-R and higher resolution respectively. Let $z(a,\theta)$ be the cost function. Since the IS are noiseless with respect to their set of distinct states, the expected cost with a system that provides partition $\{\theta\}$ is given by

$$\sum_{\theta \epsilon \Theta} \min_{a \epsilon [0,A]} z(a,\theta)p(\theta)$$

$$= \sum_{\theta_1 \epsilon s_1} z(a_1,\theta_1)p(\theta_1) + \sum_{\theta_2 \epsilon s_2} z(a_2,\theta_2)p(\theta_2) + ...$$

where a_i is the optimal action corresponding to s_i. With the A-R resolution, the expected cost is

$$\sum_{s_i \epsilon S} \min_{a \epsilon A} \sum_{\theta_i \epsilon s_i} z(a,\theta_i)p(\theta_i | s_i)p(s_i)$$

Note that $p(\theta_i | s_i)p(s_i)$ is equal to $p(s_i | \theta_i)p(\theta_i)$ and that $p(s_i | \theta_i) = 1$ for all $\theta_i \epsilon s_i$. Therefore, the two expected costs above are equal.

Discussion: Once the A-R level of detail is reached, more details are of no consequence to the decision context. Therefore, any additional information is undesirable because of the extra cost of more detailed information and the processing load placed on the DM.

Proposition 6: For systems that are noiseless with respect to their own state partitions, A-R partition is "weakly coarser" (i.e., never finer) than P-R partition.

Proof: Suppose not. Assuming that A-R partition is finer than the P-R partition, let $\{\theta\}$ and $\{s_i\}$ (in Proposition 5) be the A-R and P-R partitions respectively. Without loss of generality, assume that the A-R element $\{s_i\}$ consists of two P-R elements, θ^1_i and θ^2_i. Let a^* and a^{**} be the optimal actions for the states θ^1_i and θ^2_i respectively. From P-R considerations, we have $z(a^*,\theta^1_i) = z(a^*,\theta^2_i)$ and $z(a^{**},\theta^1_i) = z(a^{**},\theta^2_i)$.

From A-R considerations, $z(a^*,\theta^1_i) < z(a^{**},\theta^1_i)$ and $z(a^{**},\theta^2_i) < z(a^*,\theta^2_i)$. This leads to a contradiction.

Discussion: Since more detailed information is generally more costly, Proposition 6 indicates that for a class of decision problems, the A-R resolution is less detailed than the P-R resolution and is therefore cheaper to obtain. Propositions 5 and 6 provide direct guidelines for selecting the information content in IS design.

Next we turn to the subsystem level of the IS and study the design tradeoffs involved.

6. INSIDE THE IS BLACK BOX

6.1 Subsystem Characteristics

Conceptually, an IS may be represented as a collection of the following subsystems: monitoring, storing, processing (transformation), retrieving and transmitting subsystems (see Marschak 1971). These are the fundamental information handling activities, one or more of which can be identified in every IS. For example, a simple database management system consists of storing, processing and retrieving subsystems.

The monitoring subsystem samples states of the world. For example, machine loading, operator capacity and maintenance routines may be monitored by the scheduling subsystem of the MRP-based IS. The processing subsystem processes the monitoring data to create new information (e.g., the generation of parts list from customer order information) and/or transforms the monitoring data into aggregate reports. The parts requirement subsystem of the integrated MRP system is an example of the processing subsystem. It takes as input order and forecasting information and generates (through processing) raw material requirements. The exact sequence of subsystems is not the same for every IS.

Each subsystem may be considered as an individual system and described by certain attributes which are referred to as subsystem characteristics. For example, like the entire IS itself, the monitoring subsystem has accuracy, frequency, resolution, etc., as its attributes. These attributes are in turn determined by the design variables of the monitor. The general relationships between subsystem characteristics and signal attributes are discussed in the balance of this section.

The accuracy of each subsystem may be represented by a likelihood function relating the inputs and outputs of the subsystem. For a serial architecture, let $\{s_i\} = S_i$ denote the input set of distinct states for subsystem $i, i=1,2,...,n$. Note that $\{s_i\}$ is also the output set of stage i-1 for $i=2,3,...,n$. Let $\lambda(s_{i+1} | s_i)$ denote the probability of the output state being s_{i+1}, given that s_i is the input. If a subsystem is noiseless and does not induce a change in resolution, then $\lambda(.|.)$ denotes an identity transformation. For example, an ideal transmission subsystem should have this property.

The signals of the IS are generated by the last subsystem, n. Combining the transitional probabilities for each subsystem, the conditional probability of the signal being y, given that the input of subsystem 1 is s_1, is obtained as

$$\lambda(y|s_1) = \int_{s_2 \in S_2} \cdots \int_{s_n \in S_n} \lambda(y|s_n)\lambda(s_n|s_{n-1})\ldots\lambda(s_2|s_1)$$

However, the DM is generally interested in the output set $\{s_k\}$ of the processing subsystem, k. Therefore, the relevant likelihood function is $\lambda(s_{k+1}|y)$, and is given by

$$\int_{s_1 \in S_1} \lambda(s_{k+1}|s_1)\left[\lambda(y|s_1)p(s_1) \;/\; \int_{s_1 \in S_1} \lambda(y|s_1)p(s_1)\right]$$

For example, s_1 may denote demand for each item, while s_{k+1} may denote total demand for a subset of items. Thus, the accuracies of the individual subsystems can be related to the overall likelihood function for the IS.

The signal resolution of the IS is bounded by the subsystem with the lowest resolution. For example, the monitoring subsystem may be sensitive to demand of each item on each day, while the processing subsystem may aggregate this information into weekly demand data for a group of items.

The timing of a signal from the IS is determined by the activity durations of the individual subsystems and queueing times between activities. The signal reporting frequency depends on the activity and queueing times and also on the frequency of the monitoring subsystem. The signal monitoring time is determined by the sampling time of the monitor.

6.2 Relating Design Variables to Subsystem Characteristics

Since the subsystems are relatively independent of one another in terms of their subsystem characteristics,[5] the problem of relating design variables to signal attributes reduces to finding relationships between characteristics of each subsystem and its design variables. It is not possible to have one universal model for relating design variables and subsystem characteristics in any IS. Rather, the models have to be chosen depending on the IS type. For example, queueing models may be used to relate design variables such as the number of processors, batch size and permissible queue length to the average waiting time in the order processing subsystem of the MRP-based IS, while regression may be appropriate in relating the number of error detection mechanisms to the frequency of missing information in the transmission subsystem. Economic production theory may also be useful in establishing linkages between design variables and subsystem characteristics (see Kriebel and Raviv 1980). Next, we discuss a structured technique for setting the design variables of an IS.

7. SETTING DESIGN VARIABLES: "DOMINANCE ANALYSIS"

What should be the IS design variable values, given a particular decision setting? Consider an existing IS with certain signal attributes. Is the current design optimal? If not, how should the design parameters (such as processing capacity and number of error detection mechanisms, etc.) be modified? We use a structured technique (we call it "dominance analysis") to address this problem. The basic principle is to narrow down the design parameter space by successively eliminating signal attributes, subsystem characteristics and design variables that do not cause a substantial improvement in payoff. The three level hierarchy allows us to deal with a few variables at a time, as we move to lower levels of increasing details. There is some risk of suboptimization in this approach, but the tradeoffs between computational simplicity and efficiency become evident. Several variations of "dominance analysis" are possible. One such technique is outlined below.

1. We start from the DM's side, since starting with the large number of IS design variables makes the analysis difficult. Consider the intrinsic attributes one at a time and examine their effects on the DM's payoff as outlined in Section 5. If the payoff remains constant (e.g., this can happen with signal timing if the action set is time invariant over the time period of interest) or decreases (e.g., this can occur if the current signal resolution is the same as that of the A-R set of states) with changes of an attribute value, then eliminate it. If the effect on payoff is "insignificant" for one or more attributes, then eliminate the same.

2. Turn to the subsystem level. Vary the subsystem characteristics one at a time and note their effects on the signal attributes (as outlined in Section 6) that were not eliminated in step 1. The aim here is to identify "bottlenecks" at the subsystem level.[6] If certain subsystem characteristics are found to be insensitive in terms of their effects upon the signal attributes, they are eliminated.

3. For each subsystem characteristic not eliminated in step 2, identify the corresponding design variables. As in step 2, vary the design variables one at a time and eliminate the "insensitive" ones. Sometimes a change in a design variable may necessitate a change in some other design variable(s) for technological reasons. For example, an increase in the number of order processors in an integrated production control system may have to be accompanied by an increase in the number of terminals for entering order information. In this case, the two design variables have to be considered in tandem in the analysis of the existing system. Also, a change in a design variable may affect several signal attributes. For example, increasing the number of error detection stages changes both accuracy and

signal timing. At the end of this step, we have a small set of "sensitive" design variables.

4. Let V = {v} be the set of sensitive variables found in step 3. Let the signal attributes be denoted by SA = {sa}. Let the DM's payoff function be P = $P(sa_1,sa_2,...)$. The functional form of P has been discussed in detail in Section 5. Since {v} is the set of sensitive design variables, we can also write P as $P(v_1,v_2,...)$ through a mapping between {sa} and {v}. With the sensitive design variables and their impacts on payoff identified, we turn next to the cost side of the analysis, assuming that the payoff and cost are separable.

5. Generally, the cost of implementing and operating the system with new design variable values is not known in advance. What is known with certainty is the cost at the current operating point $v_c = (v_{1c},v_{2c},...)$, where the subscript c refers to the current levels. Instead of assuming a known cost function for the entire design space, we only assume that the partial cost derivatives (with respect to the sensitive design variables) are known at v_c. With this knowledge, a second order Taylor series expansion gives the approximate cost $C(v_n)$ at a new operating point $v_n = (v_{1n},v_{2n},...)$ in the neighborhood of v_c. More formally, let $\Delta v_i = v_{in} - v_{ic}$ denote the change in the variable v_i.

   Let the operator

   $$\xi = \Sigma_i \Delta v_i \frac{\partial}{\partial v_i}$$

   such that

   $$\xi C = \Sigma_i \Delta v_i \frac{\partial C}{\partial v_i}.$$

   The approximate cost at v_n is given by $C(v_n) = C(v_c) + \xi C(v_c) + \quad \xi^2 C(v_c)$. The new operating point can be chosen by considering the region in the design space where the increase in payoff starts to saturate and the cost of the corresponding design change begins to rise sharply.

The above procedure simplifies the design modification process by eliminating relatively insensitive attributes, subsystem characteristics and design variables before analyzing the payoff related tradeoffs (steps 4 and 5). It thus helps narrow down the search space and increases the accuracy of the payoff and cost estimates. At the same time, however, optimality of the solution cannot be ensured due to the fact that the intrinsic attributes and subsystem characteristics are considered one at a time.

The following examples show how a change in a design variable may affect multiple signal attributes. Say the loading of machines on the shop floor are sampled at time t. Thus, the sampling time of the monitoring subsystem (which is a design variable for the monitor) is t. In this case, t is also the monitoring time, defined earlier as a signal attribute.[7] Let p be the processing time necessary to generate an updated production schedule from the monitoring data. Thus the revised production schedule is available at time t+p. Say a DM uses this information to decide on the amount of raw materials to order. Let the maximum amount that can be ordered be time variant and be denoted by

$$A(t), \quad \frac{\partial A}{\partial t} < 0.$$

Let τ be the P-R monitoring time. If the actual sampling time $t \neq \tau$, then t should be changed. However, note that changing t affects the signal timing in addition to the monitoring time itself. This is an example of a change in a single design variable causing a change in multiple signal attributes. If $t < \tau$, then increasing t improves the payoff on one hand due to increased signal "relevance" and on the other hand possibly reduces the payoff due to the delayed signal timing (which affects the amount that can be ordered). Without considering the cost side, the optimal choice of sampling time is given by

$$\min_t \left[\int_{y \in Y} \min_{a \in [0,A(t+p)]} \int_{s^t \in S} \int_{s^\tau \in S} z(a,s^\tau_i)p(s^\tau_i|s^t_j)\lambda(s^t_j|y)p(y)\right]$$

where t affects the action set [0,A(t+p)] and the relevance of the signal as encoded in $p(s^\tau_i|s^t_j)$.

Another example of a design modification leading to a change in multiple signal attributes is the tradeoff between accuracy and signal timing. When uncertainty reduces over time, earlier signals are less accurate than later ones. Thus on one hand, the expected cost decreases with later signals due to the increase in accuracy, while on the other, it can increase due to a possible reduction in the action set. The relevant design issue is to synchronize the system to generate a signal at a time such that the DM's cost is minimized. The choice of signal timing with time varying likelihood function and action set is given by

$$\min_t \left[\int_{y \in Y} \min_{a \in [0,A(t)]} \int_{s \in S} z(a,s)\lambda_t(s|y)p_t(y)\right]$$

8. CONCLUSIONS

This paper has attempted to provide a consistent, theory-based analytical framework for the evaluation of alternative IS designs and modification of existing system designs to better match the characteristics of the decision setting.

In the process, a mathematical model of information quality has been developed. Certain properties of this quality model with direct implications for system design have been derived. The proposed model captures in a rigorous manner the essence of numerous dimensions of information value found in the MIS evaluation literature. A decision-theoretic method for measuring the impact of information quality differential upon the DM's payoffs has been illustrated. A three-level hierarchy consisting of signal attributes, subsystem characteristics and design variables has been defined and a cost-benefit framework for design modifications has been established through a structured technique called dominance analysis.

An interesting application of the proposed framework would be the measurement of the impact of alternative system designs upon decisions in the domain of production management. Information acts as an input to control-related decisions at various stages of any production system. The quality of information affects decision outcomes in various ways, ranging from excess raw materials purchase through production backlog to wrong shipments. For this purpose, the MRP-based IS of a real-world production function has been studied. A sequel paper by Barua and Ow (1988) describes the applicability of the current framework to the purchasing section of the production function.

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10. ENDNOTES

1. More precisely, less detailed than Marschak's (1963) payoff relevant description of states.

2. The concept of payoff relevance was introduced by Marschak (1963). Roughly speaking, it refers to the level of detail in the information that is sensitive to the DM's payoff. In this paper, we generalize the concept to include all attributes of information.

3. For clarity, suppose we are sampling independent observations $y_1,..., y_n$, from a population whose probability function $f(y;\ \beta)$ involves one parameter, β. The joint probability function of the sample observations ("signals") is

$$h(y_1,..., y_n) = \pi^{n}_{i=1} f(y;\ \beta) = \lambda(\beta)$$

   That is, when the joint probability function is viewed as a function of β, given the observations, it is called the **likelihood function** $\lambda(\beta)$.

4. Marschak and Radner assume that the information structures are noiseless with respect to their set of distinct states.

5. The subsystem characteristics are intrinsic properties of the subsystems. For example, the accuracy of the processing subsystem is independent of the accuracy of the transmitting subsystem, although they may handle the same data set.

6. For example, all but one subsystems may be noiseless and still the noisy subsystem may introduce significant noise in the signals.

7. For this simple case, the intermediate level of subsystem characteristics is not necessary.