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ABSTRACT

In this paper, we use an information economics approach for analyzing information systems (IS) that are used by multiple decision makers (DM) for making inter-related decisions in a cooperative environment. A decision setting is considered where there may be a precedence relationship between actions, and where one DM's action may be constrained by others' actions. Moreover, an individual DM may not have full information on other DMs' decision parameters. Several interesting results emerge from the analysis. In a two-stage, cooperative decision setting involving a purchasing and a production function, the interactions between the two decisions, and the impact of the IS shared by the DMs on their overall performance are studied. Using team theory, it is shown that when the first DM does not have full information on certain decision parameters of the second DM, the overall cost may increase with a more accurate IS, even when higher accuracy can be obtained for free. The optimal level of informational detail for the two decision makers is studied in conjunction with restricted action sets. We find that the level of detail that can be effectively utilized by the team is determined only by the action set of the second DM. This result provides a basis for determining the information requirements of the DMs as a function of their context parameters. The issue of updating information for the two DMs is also addressed. Endogenizing updating frequency as a decision variable, we show that higher updating frequency of the shared IS may lead to higher cost (or lower payoff), even when the increase in frequency is obtained at zero cost. The results of the paper have implications for better design of information systems supporting distributed decision making in cooperative environments.

1. INTRODUCTION

Complex organizational activities involve coordination and communication among multiple decision makers (DM). The widespread proliferation of information systems (IS) technology has opened up new possibilities for decision making in such complex, inter-related environments. Thus, there is a growing recognition of the importance of designing distributed computing systems that integrate different decision making units of a company. Related system design issues that must be addressed include the effectiveness of communication channels between the DMs, the type and accuracy of information to be provided to each DM, and the appropriate frequency of updating information.

While there is a large body of literature on the technical aspects of IS for enhancing coordination among decision makers, the analyses of such IS from the economic perspective have not been widely conducted in the MIS literature. As a consequence, many economics related design issues are not well-understood at this point in time. For example, what is the optimal level of informational detail of an IS in an inter-related, multi-person, cooperative decision making environment? Is more accurate information at least as valuable as less accurate information in the above environment, where a DM may not fully know certain decision parameters of other DMs?[1] What is the optimal information updating frequency for IS that support inter-related decisions? In this paper, we use the principles of information economics and team theory to investigate some of these questions, and to derive managerial guidelines for better design of shared IS.

The above design issues may be addressed by taking account of the value of distributed information to the DMs involved. The goal of this paper is to provide insights into the nature of the design solutions that would be obtained by solving large-scale realistic models. Accordingly, we explore a simplified model from which analytic solutions can be obtained. In this sense, the paper follows the tradition of micro-economics rather than operations research.

In particular, we consider a manufacturing environment involving a purchasing and a production manager. Using a shared information system, they act as a team and attempt to minimize the total cost of shortage and excess of raw materials and finished goods. While the paper is geared to this production setting, the results obtained from the analysis may be generalized to any multi-person decision environment with the following characteristics:

- A precedence relationship exists between decisions, whereby one DM's action becomes an input to the next DM's decision.

- A DM's action may be constrained by others' actions, since the objective is to minimize (or maximize) the overall cost (or payoff).

- A DM may not have full information on certain decision parameters of the other DMs.

The basic results of the paper may be summarized as follows: When the first DM does not have perfect information on certain decision parameters of the second DM, the overall cost incurred by the team may *increase* from the use of a more accurate (i.e., less noisy) IS, even when the increase in accuracy is obtained for *free*. This result is in sharp contrast to the single DM case, where more accurate information is at least as valuable as less accurate information. It poses some important IS design considerations for inter-related decision settings. The optimal level of informational detail for the two DMs is investigated for the case where one of the DM's action set is restricted. We find that the optimal level of detail for the team is determined *only* by the action set of the second DM: i.e., irrespective of whether or not the action set of DM1 is restricted, the level of detail that can be effectively utilized by the team is solely determined by the action set of DM2. The extent of interaction between the two decisions and its impact on the usage of the IS are studied through the choice of ordering and production times. Lastly, the issue of selecting an updating frequency for the IS is addressed. It is shown that in the absence of synchronization between the subsystems of the IS, a higher updating frequency does not guarantee a lower cost for the team, even when the increase in frequency is obtained at zero cost. The results of the paper emphasize some central issues in the design of shared information systems, such as the effect of inter-dependency of decisions on the maximum team performance attainable with alternative IS designs, and the tradeoffs between organizational and IS parameters.

The balance of the paper is organized as follows: In section 2, we present a brief survey of the relevant MIS and information economics literature. It reveals a gap in the study of the economics of shared information systems, provides the motivation for this paper. The production environment, the IS used by the two DMs, and their decision parameters are described in section 3. Section 4 contains the derivation of the results, and also includes numerical examples and intuitive justification to support the findings. Planned extensions and enhancement of the basic model are outlined in section 5. Managerial implications of the study and concluding remarks are provided in section 6.

2. MOTIVATION AND PRIOR RESEARCH

With organizations becoming increasingly complex, essential managerial activities are taking the form of inter-related decisions involving coordination, collaboration, and communication across multiple decision makers. As a result, the design, development and evaluation of information systems that can support cooperative decisions have become major concerns in MIS research. Applegate et al. (1991) broadly refer to such IS as organizational computing systems and define their scope:

> Organizational computing involves the development, operation, and evaluation of computing systems explicitly aimed at directly aiding the performance of multiple participants engaged in a common task or pursuing a common goal.

There is a growing body of technical and behavioral literature on organizational computing. The topics include computer supported collaborative work, groupware, negotiation support systems and coordination technology (Applegate 1991; Ellis, Gibbs, and Rein 1991; Kraemer and King 1988; Turoff and Hiltz 1982). However, the MIS literature is particularly lacking in terms of studies focusing on the economic aspects of design and evaluation of organizational computing systems. Applegate et al. recognize the need for information economics based studies on assessing the value of knowledge and computer-based systems for managing the knowledge in the context of organizational computing.

Although somewhat restrictive in nature, information economics is a well-developed theory for assessing the value of alternative information systems (Barron and Saharia 1990). In our present context, *team theory*, a subfield within information economics (originally developed by Marschak and Radner 1972), provides a starting point for analyzing the design of information systems in a cooperative environment. A team is composed of multiple decision makers taking individual actions on the basis of their information, which they receive through their own information structures.[2] All team members attempt to maximize a common payoff function. The explicit recognition and optimization of a single objective make team theory particularly appealing for the evaluation of cooperative information systems. However, we note that typical multi-person environments have certain characteristics which are not considered in team theory formulations. For example, explicit interactions between the actions of various decision makers have not been studied in team theory.[3] Similarly, a DM's knowledge of the decision parameters (e.g., the available action set) of other DMs, and its impacts on his/her decision, have not been addressed. These are, however, some of the issues that are central to the development of successful organizational computing systems for enhancing cooperative decision making. In this paper, we adopt the joint optimization approach of team theory to study some economic aspects of information systems used in making inter-related decisions.

It is useful to briefly describe the abstraction of an IS used in this study. Marschak and Radner (1972) characterized an information structure by the *fineness* (or equivalently, *coarseness*) of the information provided by the structure. Formally, it is expressed through a *likelihood function*, which for discrete values is a matrix of conditional probabilities, $[\lambda(y)|\theta)]$ where $\{y\}$ is the set of signals that can be received from the IS, and $\{\theta\}$ is the set of states of the world (see McGuire (1972) for a discussion on the comparison of information structures). More recently, Barua, Kriebel and Mukhopadhyay (1989) and Barua (1991) have enhanced the attributes of information through the development of a formal, multi-dimensional model of information quality. In this paper, we consider three attributes — signal accuracy, signal timing, and information updating frequency — and study their impacts on the performance of a team in an inter-related environment.

Since we use fineness (or coarseness) of information in our analysis, it is useful to translate these terms into the associated design issues that IS specialists would face. If information is arranged in the form of a relational table, the measurement scale for each field in the table and the total number of fields jointly determine the fineness of the information contained in the table. For example, a field's values could simply be called "high," "medium," and "low" in referring to the demand for a finished product. In effect, this is a partitioning of the real number system. A more precise (i.e., finer) scale would be obtained by using integers. Similarly, removing a field (say, sales) from the table reduces the fineness of the state space partition, since now there is no information available on the field in question. The abstraction in terms of fineness helps us derive analytic solutions for the inter-related team environment in the subsequent sections.

3. THE DECISION ENVIRONMENT AND THE IS

In order to provide a context for our discussions, we consider a simple manufacturing environment with two DMs: a purchasing manager (DM1) and a production manager (DM2). They use an integrated Material Requirement Planning (MRP) system for making purchasing and production decisions. The MRP system has a *demand forecasting subsystem*, which provides information on the demand for finished products. The gross raw material requirements are computed by a *parts requirements subsystem* using information on the demand for finished products and the Bill of Materials. We do not consider inventory levels directly in the computation of raw material requirements. This may be the case in a just-in-time environment, where there may be a penalty for excess raw materials in an attempt to minimize inventory, requiring closer coordination between the decision makers.

We model the purchasing and production decisions as a team with a common cost function. We consider a single finished product which requires k units of a raw material. The results derived in the following sections can be generalized to products involving multiple types of raw materials. Let θ_f and θ_r denote the true demand for a finished product and raw material requirements respectively. Then, according to the above assumption, $\theta_r = k\theta_f$. Let a_f be the amount of finished goods to be produced (DM2's decision), and a_r be the amount of raw material to be purchased (DM1's decision). Let us assume a quadratic cost function which is given by

$$z(a_f, \theta_f, a_r, k) = c_f(a_t - \theta_f)^2 + c_r(a_r - a_f k)^2$$

where $c_f(a_t - \theta_f)^2$ is the cost of shortage or excess of finished goods, and $c_r(a_r - a_f k)^2$ is the cost of excess raw materials. We note that the above cost function only deals with the efficiency of managing raw material and finished goods inventory (which is directly affected by an information system), and does not take into account other components such as raw material cost and production cost.

Quadratic costs have several drawbacks, including the identical treatment of excess and shortage situations. However, it allows for algebraic manipulation, and is a widely used functional form. While we use the above cost function for analytical tractability, the results of the paper are not artifacts of the specific quadratic form, being based on more general intuitions.[4]

The above formulation imposes a constraint on DM2's action: $a_f \leq a_r/k$. At a later point in the analysis, we will introduce some temporal aspects of the IS used by the DMs. In that case, it will be useful to consider a production rate for finished goods, P, a starting time for the production process, t (to be determined endogenously), and an ending time, t_e (specified exogenously, such as a deadline), for the production process. Thus, there will be an additional constraint on DM2's decision: $a_f \leq (t_e - t)P$.

Our intent in this paper is to study the effect of the *interaction* between the decisions on the best team performance attainable with alternative IS. As a result, we do not incorporate actions on the part of DM1 and DM2 that have no direct interaction. For example, DM1 may also take an action regarding the selection of a supplier based on information regarding the quality supplied. This action does not affect DM2's decision on the quantity of finished goods. Similarly, based on information regarding the past performance of production equipment and personnel, DM2 may have to decide on the amount of inspection for production defects in the finished goods, which is independent of DM1's actions. Thus, our attention is purposely focused only on interacting decisions.

It is also important to note that the above scenario only serves to highlight the utility of a set of results that can be applied to a broader variety of decision contexts. The manufacturing environment, however, provides some of the characteristics of inter-related decisions we wish to study. First, there is a precedence relationship between the decisions (the purchasing decision precedes the production decision). Second, DM2 is constrained by the amount ordered by DM1. At the same time, DM1 must consider the decision parameters of DM2 (since the overall cost must be minimized), and is therefore implicitly constrained by the latter. Third, DM1 may not have full knowledge of all the decision parameters of DM2, either due to lack of communication, or due to the dynamic nature of the parameters themselves.

The information system reports on θ_f and θ_r. Let $\{y_r\}$ and $\{y_f\}$ be the information (signal) sets corresponding to partitions of $\{\theta_r\}$ and $\{\theta 12f\}$ respectively. Note that the mapping between $\{y_f\}$ and $\{y_r\}$ is not necessarily one-to-one when the time dimension is considered. Demand information and raw material requirements information may be updated at different times (when there is a lack of synchronization between the subsystems of the IS itself). However, for the static decision making environment, we will assume that knowing y_f and k enables one to compute the corresponding y_r.

4. RESULTS

The results of this study may be broadly divided into static and dynamic categories, depending on whether or not they address temporal issues.

4.1 Decisions in a Static Environment

To understand the motivation for having two DMs, we note that if all the parameters of the two decisions are fully known to one of the DMs, then the decisions could be centralized. In that case, the optimal decisions for a given IS can be determined by using the dynamic programming approach. We first derive the optimal decisions for a static environment, where the production rate, P, is large (i.e., P does not pose a constraint on DM2's decision regarding the amount to be produced). We use the following notation:

$\lambda(.|.)$ is a conditional density or mass function (the likelihood function).

$p(.)$ is a density or mass function defined over the states and/or signals.

Proposition 1: *When the production rate P is not a constraint on the actions of DM1 and DM2, the optimal actions are given by*

$$a_r^* = k \int_{\theta_f \in \Theta_f} \theta_f \lambda(\theta_f | y)$$

$$a_f^* = \int_{\theta_f \in \Theta_f} \theta_f \lambda(\theta_f | y)$$

where y is the signal on the demand for finished goods, and where the integral sign stands for a generalized summation operator.

Proof: Following a dynamic programming approach, we first optimize the second decision. Given any signal y on the demand for finished goods, and a_r, the action taken by DM1, DM2's choice may be stated as

$$\underset{a_f}{\text{minimize}} \int_{\theta_f \in \Theta_f} [c_f(a_f - \theta_f)^2 + c_r(a_f - a_r k)^2 + L(a_f - a_r/k)]\lambda(\theta_f|y)$$

where L is the Lagrange multiplier. Differentiating with respect to a_f and setting to zero, we have

$$L = 2\, c_r k(a_r - a_f k) - \int_{\theta_f \in \Theta_f} 2c_f(a_f - \theta_f)\lambda(\theta_f|y)$$

Differentiating the cost function with respect to L and setting to zero, we have $a_f = a_r/k$. Using this value of a_f in the cost function, and differentiating with respect to a_r,

$$\frac{2c_f}{k} \int_{\theta_f \in \Theta_f} (a_r/k - \theta_f)\lambda(\theta_f|y) = 0$$

Thus, the Lagrange multiplier, L, is zero, indicating (for this minimization problem) that it is not limiting the objective function. The intuition is that DM1 calculates DM2's requirements (since they are trying to minimize the team cost function) and orders exactly that amount. Therefore, we use an unconstrained optimization approach to derive the desired results. DM2's choice is given by

$$\underset{a_f}{\text{minimize}} \int_{\theta_f \in \Theta_f} [c_f(a_f - \theta_f)^2 + c_r(a_r - a_f k)^2]\lambda(\theta_f|y)$$

Differentiating with respect to a_f, we have

$$a_f = \frac{c_r k a_r + c_f \underline{\theta}_f}{c_f + c_r k^2}$$

where $\underline{\theta}_f = 4\int_{\theta_f \in \Theta_f} \theta_f \lambda(\theta_f|y)$

Let $A = c_r k$, $B = c_f \underline{\theta}_f$, and $D = c_f + c_r k^2$. Substituting the value of a_f^* in the cost function, DM1's choice, problem (for a given signal y, and k) may be stated as:

$$\underset{a_r}{\text{minimize}} \int_{\theta_f \in \Theta_f} [c_f(\frac{Aa_r + B}{D} - \theta_f)^2 + c_r(a_r - k\frac{Aa_r + B}{D})^2]\lambda(\theta_f|y)$$

Differentiating and setting to zero, we have

$$c_f A^2 a_r + c_r(D - Ak)^2 a_r - c_r k B(D - Ak) + c_f AB - c_f AD\underline{\theta}_f = 0$$

$$\text{or } a_r[c_f c_r^2 k^2 + c_r c_f^2] = [c_r c_f^2 k + c_f c_r^2 k^3]\underline{\theta}_f$$

$$\text{or } a_r^* = k\underline{\theta}_f = k\int_{\theta_f \in \Theta_f} \theta_f \lambda(\theta_f|y) \qquad \circ$$

Discussion: The above proposition shows how both of the decisions could be made by one DM with the knowledge of all relevant parameters, with the same expected cost as that of the distributed case. However, from a realistic viewpoint, it is difficult for one person to have full knowledge of all decision parameters. For example, the purchasing manager may not have perfect information on the maintenance schedule of the production equipment, which in turn may determine the true production rate. Similarly, in a dynamic environment, certain parameters may change so often that communication-based centralization of the two decisions may not be a feasible or cost effective solution.[5] As an illustration, there may be an unexpected equipment breakdown or an unavoidable change in the production schedule due to prioritization of some specific orders.

Even in the case of decentralized decision making, it is still optimal for the two DMs to follow the decision rules outlined in Proposition 1, but with their respective knowledge on each other's decision parameters. Thus, for example, when DM2 does not have full information on DM1's parameters, following the above decision rules will still lead to the least expected cost that could be achieved without complete communication between the two DMs. We will utilize these decision rules throughout the paper.

Also note that the above decision rules were derived by assuming that the two DMs receive two signals that have a one-to-one correspondence. That is, for any signal received by DM1, the corresponding signal for DM2 can be identified. If DM2 receives a more accurate signal from the IS after DM1 has taken an action, then DM2 can determine the optimal decision with DM1's action and the new signal as given.[6] Similarly, due to a lack of synchronization between the update of demand and raw material requirements information, DM1 and DM2 may take actions based on signals which do not have a one-to-one correspondence.

Next, we study the impact of the accuracy of the IS on the performance of the team, when DM1 may not have full knowledge of DM2's parameters. In particular, we consider the case where DM2's action set is temporarily restricted (say, due to machine breakdown or maintenance), and where due to lack of communication DM1 continues to believe that DM2 has an unrestricted action set.

Proposition 2: *If DM2 has a restricted action set, and if DM1 does not have this information, then the overall cost may increase when DM1 uses a more accurate system, even when the increased accuracy is obtained for free.*

Proof: By construction. Consider the case where a perfect (noiseless) information system is used by DM1. Let the action set of DM2 be restricted to $\{0, n\}$, with $\theta_f \in \{0, 1, ..., n\}$. Let $p(\theta_f) = p \ \forall \ \theta_f \in \Theta_f$, i.e., the density over states is uniform. If there is no communication between the two DMs, DM1 takes an action $a_r = \theta_f k$ corresponding to the signal for θ_f (since the system is perfect).

The expected cost is

$$c_f \sum_{\theta_f \in \{0, 1, ..., n-1\}} \theta_f^2 p(\theta_f) + c_f k^2 \sum_{\theta_f \in \{0, 1, ..., n-1\}} \theta_f^2 p(\theta_f)$$

The above expression for the expected cost is explained by the fact that DM2's action is 0 for $\theta_f \in \{0, 1, ..., n\text{-}1\}$, and n for $\theta_f = n$. Now consider a noisy system which provides a coarser state space partition $\{[0, n\text{-}1], n\}$ with a signal set $\{y_1, y_2\}$ corresponding to the two partition elements. For signals y_1 and y_2, DM1 orders

$$k\sum_{\theta_f \in \{0, 1, ..., n-1\}} \theta_f \lambda(\theta_f|y_1)$$

and n respectively, while DM2 takes actions $a_f = 0$ and n respectively.

The expected cost with the noisy system is given by

$$c_f \sum_{\theta_f \in \{0, 1, ..., n-1\}} \theta_f^2 \lambda(\theta_f|y_1)p(y_1)$$
$$+ c_f k^2 \{\sum_{\theta_f \in \{0, 1, ..., n-1\}} \theta_f^2 \lambda(\theta_f|y_1)\}^2 p(y_1)$$

The difference in expected cost between the noisy and the perfect system is

$$c_f k^2 \{\sum_{\theta_f \in \{0, 1, ..., n-1\}} \theta_f \lambda(\theta_f|y_1)\}^2 p(y_1)$$
$$- c_f k^2 \sum_{\theta_f \in \{0, 1, ..., n-1\}} \theta_f^2 p(\theta_f)$$

Note that $\lambda(\theta_f|y_1) = 1/n$ and that $p(y_1) = n/(n + 1)$. Thus the above difference is given by

$$c_f k^2 \{\frac{n(n - 1)^2}{4(n + 1)} - \frac{n(n\text{-}1)(2n - 1)}{6(n + 1)}\}$$

which is negative. ●

Numerical example: Let the state space be $\Theta_f = \{0, 1, 2, ..., 99\}$. Let $p(\theta_f) = .01 \; \forall \; \theta_f \in \Theta_f$. Let $c_f = c_f k^2 = 1$. Also let the restricted action set of DM2 be given by $\{0, 99\}$. Consider a perfect (noiseless) system. The expected cost after using the system is

$$\sum_{\theta_f \in \{0, ..., 98\}} \theta_f^2 p(\theta_f) + \sum_{\theta_f \in \{0, ..., 98\}} \theta_f^2 p(\theta_f)$$

$$= .01 \times 2 \times \frac{98 \times 99 \times 197}{6} = \$6370.98$$

Consider a coarser system with state space partition $\{[0, 98], 99\}$. With this system, the expected cost is

$$\sum_{\theta_f \in \{0, ..., 98\}} \theta_f^2 \lambda(\theta_f|y_1)p(y_1) + (49)^2 p(y_1)$$

$$= .01 \times \sum_{\theta_f \in \{0, ..., 98\}} \theta_f^2 (49)^2 \times .99$$

$$= \$5562.48$$

Discussion: The intuition behind the result is as follows: With the perfect system, DM1 orders an amount equal to k times the true demand for finished products, while DM2 cannot change his/her action for every state of the world because of the restricted action set. As a result, there will be an excess of raw materials which increases the total expected cost. With the coarser IS, DM1 is forced to order an average amount, which results in a lower cost figure. The proposition implies that the well-known result of a more accurate system being at least as useful (valuable) as a less accurate system (for the single decision maker case) cannot be taken for granted in a multi-person environment with inter-related decisions. In particular, when the action set of a DM is not known fully to the other DM(s), the overall cost (or payoff) can increase (decrease) with the use of a more accurate (less noisy) system.

One important system design implication is that in a dynamic environment, where the DMs' action sets may change often, the communication linkages between DMs must be investigated/improved before contemplating an increase in the accuracy of the IS which reports on the demand for finished products and the corresponding derived demand for raw materials. In the absence of an effective communication subsystem, an improvement in the accuracy of demand and raw material requirement information may even have a negative effect on team performance. The communication system between the DMs need not remain active on a constant basis. From an economic standpoint, it should be triggered only when there is a *relevant* change in DM2's action set. A change in DM2's action set is relevant for the team iff it changes DM1's optimal action for at least one signal from the IS. Communicating changes that do not affect DM1's choice only adds to the communication cost without a corresponding increase in payoff. This notion of *action relevance* can be generalized beyond our current context, and can be used to guide the design of communication channels.

An important related issue is the value of communication between the two DMs in this context. Interestingly, the value depends not only on the difference between the true action set of DM2 and that perceived by DM1, but also on the state space partition of the IS used by the DMs. For example, the value of communication for the coarser IS (as described above) is \$2376.99 (since the expected cost to the team is \$3185.49 with perfect communication regarding DM2's action set,[7] while it is \$3185.49 for the perfect IS. Thus, in this case, a higher level of expenditure on a communication channel between DM1 and DM2 is justified for the more accurate IS. This implies that the benefits (and by extension, costs) of improving the communication subsystem and of increasing the accuracy of the IS should be considered in tandem because of the interaction between communication and accuracy.

We note that the result of Proposition 2 is not dependent on the particular form of the restricted action set (e.g., $\{0, n\}$ used in the proof and the numerical example. For instance, when DM2's action set is {0, 49, 99}, the expected cost with a perfect system is given by

$$2 \sum_{\theta_f \in \{0, \ldots, 48\}} \theta_f^2 p(\theta_f) + 2 \sum_{\theta_f \in \{49, \ldots, 98\}} (\theta_f - 49)^2 p(\theta_f)$$

$$= \$1568.50$$

Similarly, with the coarser system, the expected cost can be shown to be \$808.50, which is less than the expected cost with the perfect system.

Next we consider the problem of determining the optimal level of informational detail for the team, when one of the DMs has a restricted action set. As mentioned in sections 1 and 2, we are interested in finding the information requirements of the two DMs as a function of their decision context parameters such as the set of available actions.

Proposition 3: *If only DM2 has a restricted action set, $\{a_{fi}\}$, $i = 0, \ldots, n$, then let the optimal state space partition for the team be denoted by Z_2. If only DM1 has an equivalent action set restriction, $\{a_{fi}k\}$, $i = 0, \ldots, n$, then let Z_1 be the optimal state space partition.* Z_1 is finer than Z_2.

Proof: First, consider the case where DM2 has a restricted action set $\{a_{fi}\}$, $i = 0, \ldots, n$. Since the states of the world (demand, in this case) and the actions (amount produced) have the same units, we can use the actions to denote a particular partition of the state space. Consider a partition $\{a_{f0} + \alpha_0, \ldots, a_{f,n-1} + \alpha_{n-1}\}$ such that for all states in the interval $(a_{fi} + \alpha_i, a_{f,i+1} + \alpha_{i+1}]$ DM2 takes the same action $a_{f,i+1}$. That is, DM1 will take actions $a_{f0}k, a_{f1}k, \ldots, a_{fn}k$ corresponding to the respective elements of the above partition. With a finer partition, DM1 will still take the same actions, since the change in partition does not affect DM2's actions. Note that the total cost will increase if DM1 changes actions while DM2 doesn't. Hence the above partition is optimal for the team.

Consider the case where DM1 has an equivalent restriction given by $\{a_{fi}k\}$, $i = 0, \ldots, n$. We show that there is a benefit of making the information more detailed than the above partition. Let the true demand for finished product lie in the partition element $(a_{fi} + \alpha_i, a_{f,i+1} + \alpha_{i+1}]$. DM1 orders $a_{f,i+1}k$ corresponding to this partition element. Note that DM1 cannot change the action (due to the action set restriction) for any state in this interval. Thus DM1's action remains the same even for a finer IS. But DM2 may change his/her action when the fineness (level of detail) of information is increased. Consider an IS that provides perfect information in the interval $(a_{fi} + \alpha_i, a_{f,i+1} + \alpha_{i+1}]$. Let DM1's action $a_{f,i+1}k$ be denoted by $a_{r,i+1}$. Given this action, DM2's choice with perfect information is given by

$$\min_{a_f} \left[c_f(a_f - \theta_f)^2 + c_r(a_r - a_f k)^2 + L(a_f - a_{r,i+1}/k)\right]$$

where L is the Lagrange multiplier. Solving for L, we have

$$L = 2c_f(\theta_f - a_{r,i+1}/k)$$

Thus, if $\theta_f \leq a_{r,i+1}/k$, then the constraint is not a limitation. With any $\theta_f < a_{r,i+1}/k$, the optimal a_f will be strictly less than $a_{r,i+1}$, showing that the partition $\{a_{f0} + \alpha_0, \ldots, a_{f,n-1} + \alpha_{n-1}\}$ is not optimal when DM2 has an unrestricted action set. ○

Numerical example: Let $c_f = c_r = k = 1$, $\Theta_f = \{0, 1, 2, \ldots, 100\}$, and $p(\theta_f) = .0099\ \forall\ \theta_f \in \Theta_f$. Also, let the restricted action set of DM2 be given by {0, 50, 100}. Then the optimal state space partition for the team is given by {[0, 24], [25, 75], [76, 100]}. To see why, consider the partition element [25, 75].[8] In this interval, DM1 has a choice between 0, 50 and 100 units. For $a_r = 50$, the restricted choice of a_f is given by

$$\min_{a_f \in \{0,50\}} \left[\sum_{\theta \in \{25, \ldots, 75\}} (a_f - \theta_f)^2 \lambda(\theta \mid y_2) + (50 - a_f)^2 \right]$$

where y_2 is the signal corresponding to the interval [25, 75]. The optimal value of a_f is found to be 50, with a total expected cost of \$216.58. DM1 does not choose 0 or 100, since the total expected cost is lowest for 50. With a_f restricted to {0, 50, 100}, a finer state space partition has no additional value for the team. Even if DM2 knew the exact value (between 25 and 75) taken by the true state of the world, his/her action remains the same (= 50).

Now consider the case where DM1 has the restricted action set {0, 50, 100}, while DM2 has an unrestricted action set. We will show that a finer state space partition than the above leads to a lower expected cost. Consider a perfect system that recognizes all states between 25 and 75 units as distinct. When DM1 orders 50 units, the optimal action a_f may be stated as a function of θ_f for $\theta_f \leq 50$:

$$a_f = 25 + \theta_f/2$$

The above expression shows that there is additional value of knowing the exact state of the world. That is, with a more accurate IS (which induces a finer partition), DM2 is able to *fine-tune* the choice of a_f. For example, if the true state of the world is 25, then DM2 decides on 37.5 instead of 50 units to minimize the cost. The total expected cost is

$$[\sum_{\theta_f \in \{25, ..., 50\}} 2(25 - \theta_f/2)^2 + \sum_{\theta_f \in \{51, ..., 75\}} (50 - \theta_f)^2]p(\theta_f : \theta_f \in \{25, ..., 75\}) = \$162.43$$

Discussion: An interesting corollary that follows directly from proposition 3 is that the optimal level of informational detail for the two-person team is solely determined by the action set of DM2. That is, DM1 need not obtain detailed information when DM2 has a restricted action set. The intuition is that when DM1 has an unrestricted action set, his/her choices are still *effectively* constrained if DM2 has a restriction. Thus, more detailed information has no additional value for DM1. However, the converse is not true. Even when DM1's action set is restricted, DM2 can reduce the team cost by obtaining finer information. That is, with a finer IS, for all values of demand less than a_r/k, DM2 can choose an action which results in some excess raw material inventory (i.e., $a_f < a_r/k$), but which, nevertheless, lowers the total expected cost below what would be obtained with zero raw material inventory.

One of the key system design criteria is to provide information that is both necessary and sufficient for a given decision setting. A higher-than-sufficient level of detail does not reduce (increase) team cost (payoff), and generally costs more to obtain. Proposition 3 offers a basis for determining the relevant level of informational detail for an inter-related team. The *action relevance* criterion for each DM determines what level of detail is appropriate for him/her. For example, it can be shown that for the interval [25, 75] above, an IS which distinguishes between all states in the interval [25, 50] and none between [51, 74] provides the optimal level of detail for DM2 (when DM2 has an unrestricted action set).

4.2 Temporal Considerations for the Team

To this point, we have considered IS with stationary likelihood functions. However, in many situations, the accuracy of the signals from the IS may increase over time due to temporal resolution of uncertainty (Barua, Kriebel and Mukhopadhyay 1989). At the same time, the actions available to a DM can change[9] with time. For example, if t_e is the deadline for shipping finished goods, then the action set of DM2 at time t is given by $[0, (t_e - t)P]$. Similarly, the maximum amount that DM1 can order may also be decreasing with time.

In this subsection, we study the impact of an IS on the performance of the team, when (i) the accuracy of the IS increases with time, (ii) both DM1 and DM2 have decreasing action sets, and (iii) DM1 may not have perfect information on the production rate, P. The following characterizations are used in the subsequent analysis:

The accuracy of the IS increases continuously with time. For example, if there are two states $\{\theta_1, \theta_2\}$, and two signals $\{y_1, y_2\}$, then the conditional probabilities $\lambda(y_i | \theta_j)$, $i, j = 1, 2$, may change with time, and approach 1 for $i = j$ and 0 for $i \neq j$.

For the sake of simplicity, we assume the supplier lead time to be zero. When the assumption does not hold true, the possibility of the two DMs taking actions based on different signals has to be addressed explicitly.

Proposition 4: *If DM1 does not have perfect information on the parameter P, then the expected cost may increase by using an IS which becomes more accurate over time, even when the cost of increasing accuracy is zero.*

Proof: By construction. Let P' be the production rate perceived (or estimated) by DM1. Let $A_r(t)$ denote the maximum amount of raw materials available at time t. Let $A_r(t)$ be a decreasing function of time. For an IS that does not increase in accuracy over time (i.e., has a stationary likelihood function), DM1 will take an action at t, such that $A_r(t) = k^* \sup \{\theta_f\}$ (since waiting any longer brings in the possibility of not being able to order a sufficient amount of raw material in the event of high demand). However, when the likelihood function

$\lambda(y|\theta_f)$ changes (improves) over time, DM1 takes an action at time $t' \geq t$, since there is a possibility of improving performance with the accuracy of information. Let y_{fl} and y_{fs} be the signals corresponding to $inf\{\theta_f\}$ and $sup\{\theta_f\}$ respectively. If t' is such that

$$(t_e - t')P < \int_{\theta_f \in \Theta_f} \theta_f \lambda_t(\theta_f|y_{fl}), \text{ and}$$

$$(t_e - t')P' \geq \int_{\theta_f \in \Theta_f} \theta_f \lambda_t(\theta_f|y_{fs}),$$

then the available time period becomes a binding constraint for the second decision for all signals. That is, for all signals, DM2 will be forced to produce $(t_e - t')P$ units. However, DM1 calculates t' to be non-binding, since with the perceived production rate, P', the maximum amount that can be produced is greater than or equal to the maximum quantity that could be required upon the receipt of any signal at time t'. Thus the binding constraint increases the expected cost beyond what is obtained with a stationary IS. ○

Numerical example: Let P and P' be 20 and 30 respectively. Let $t_e = 6$, $\Theta_f = \{\theta_1, \theta_2\} = \{25, 100\}$, and $p(\theta_1) = p(\theta_2) = .5$. Let $c_f = c_r = k = 1$. Also, let the time variant likelihood function be given by $\lambda_t(y_1|\theta_1) = \lambda_t(y_2|\theta_2) = 1 - .4e^{-t/8}$. At $t = 0$, the stationary IS is the same as the non-stationary IS, with a likelihood function $\lambda(y_1|\theta_1) = \lambda(y_2|\theta_2) = .6$. Let the maximum amount that can be ordered at time t be given by $A_r(t) = 100 - 2t^2$.

For a signal y at t, the unconstrained optimal action by DM1 is given by

$$a = \sum_{f \in \Theta_f} \theta_f \lambda_t(\theta_f|y)$$

and the expected cost is given by

$$\sum_{y \in \{y_1, y_2\}} \min_a \sum_{\theta_f \in \{\theta_1, \theta_2\}} (a - \theta_f)^2 \lambda_t(\theta_f|y) p_t(y)$$

At $t = 0$, DM1's unconstrained optimal actions for y_1 and y_2 are 55 and 70 respectively, with a total expected cost of $1350. Note that the true production rate, P, does not act as a binding constraint at $t = 0$.

At $t = 3$, he corresponding actions are 45.62 and 79.37 respectively, with an expected cost of $1121.33. With DM1's information on P being 30, the production rate does not act as a constraint on the amounts to be produced. However, in reality, DM2 will be able to produce a maximum of 60 units. As a result, the expected cost will be $1496.87, which is higher than the expected cost at $t = 0$. Therefore, the expected cost is lower when the DM uses a less accurate but stationary likelihood function at $t = 0$.

Discussion: Proposition 4 and the associated numerical example show that imperfect communication regarding the production rate may increase the team cost by (i) constraining DM2 to a suboptimal action and (ii) creating excess raw material inventory.

The proposition highlights some design tradeoffs for the shared IS. With a very high P, an IS whose accuracy increases relatively slowly will perform quite well, and may indeed be an optimal choice when the cost of a rapid increase in accuracy is high. The concept may be generalized to the design of an IS for a given level of organizational resources. In section 5, however, we consider P as an organizational variable, and discuss the possibility of the joint determination of P and the IS attribute levels.

Next we investigate the effect of the accuracy of the IS on the time at which DM1 takes an action. Since the availability of raw materials must precede production, the ordering time is an important factor in ensuring that the production process is completed on time. First, we obtain a lower bound on the timing of DM1's action.

Proposition 5: *Let the signals corresponding to $sup\{\theta_f\}$ and $sup\{\theta_r\}$ be y_{fs} and y_{rs} respectively. The raw material ordering decision can be delayed at least up to a time $t^* = min\{t^*_1, t^*_2\}$, where t^*_1 and t^*_2 given by $E_{t^*_1}(\theta_f|y_{fs}) = (t_e - t^*_1)P$ and $A(t^*_2) = E_{t^*_2}(\theta_r|y_{rs})$, and where $E_t(\theta|y)$ is the conditional expectation at t.*

Proof: $E_t(\theta_f|y_{fs})$ and $E_t(\theta_r|y_{rs})$ increase with time and approach *sup* $\{\theta_f\}$ and *sup* $\{\theta_r\}$ respectively. At t^*_1, the maximum amount that can be actually produced equals the maximum amount that DM2 may possibly decide upon in an unconstrained environment. Similarly, at t^*_2, the maximum amount of raw material that can be ordered equals the maximum amount that DM1 may possibly order in an unconstrained environment. Therefore, neither DMs' action set becomes *effectively* restricted before t^*. Also, since the accuracy of the IS increases with time, there is no need to order before t^*. ○

Discussion: Proposition 5 shows the interaction between the parameters of the two DMs and its impact on a lower bound on the timing of the purchasing decision. As in proposition 4, we note the importance of DM2's knowledge of the production rate, P. Next, we derive an upper bound on the timing of the purchasing decision.

Proposition 6: *Let $t^{**} = min \{t_1^{**}, t_2^{**}\}$, where t_1^{**} and t_2^{**} are given by*

$$inf\ \{\theta_f\} = (T_e - t_1^{**})P \text{ and } A_r(t_2^{**}) = k * inf\ \{\theta_f\}.$$

Regardless of the accuracy of the IS, the performance of the team deteriorates when the purchasing decision is made after t^{**}.

Proof: t_1^{**} is the time at which the maximum amount that can be produced equals the minimum amount that could be required by DM2 upon the receipt of any signal. Similarly, t_2^{**} is the time at which the maximum amount that can be ordered equals the minimum amount that could be required by DM1. Therefore, the minimum of these two times forms a binding constraint on the team performance, and delaying the ordering decision beyond t^{**} can only increase the expected cost, regardless of the accuracy of the information received. •

Discussion: After t_1^{**}, DM2 is forced by the time constraint to produce $(t_e - t)P$ units, irrespective of the signal received. Similarly, after t_2^{**}, DM1 is forced to order $A_r(t)$ regardless of the IS used. A corollary that follows from proposition 6 is that irrespective of accuracy, any signal used before t^{**} is superior (in terms of team performance) to any signal after t^{**}. Propositions 5 and 6 indicate that the optimal purchasing time lies between t^* and t^{**}. Next we investigate the issue of updating the information provided by the IS.

4.3 Increasing the Update Frequency of the IS

In the above discussion on temporal considerations, we studied a situation where the accuracy of the IS increases continuously. The change in accuracy is directly related to the frequency of updating the current information. Thus, a continuous increase in accuracy requires continuous updating. From a design standpoint, it is useful to consider the updating frequency as a decision variable. In the present context of the manufacturing function, two updates to the IS are necessary: one for the subsystem providing information on the demand for finished products, and the other for the raw material requirements subsystem. In the proposition below, we examine the role of information updating frequency on the performance of the team.

Proposition 7: *If updates to the finished goods and raw material requirements information do not occur at the same time, a higher updating frequency of the raw material requirements subsystem may lead to higher expected cost, even when the cost of increasing the frequency is zero.*

Proof: By construction. Figure 1 shows two updating frequencies $1/\tau$ and $1/\tau'$ for the subsystem that generates raw material requirements. Let $1/\tau_f$ denote the updating frequency for the information on demand for the finished product, where $\tau < \tau_f < \tau'$.

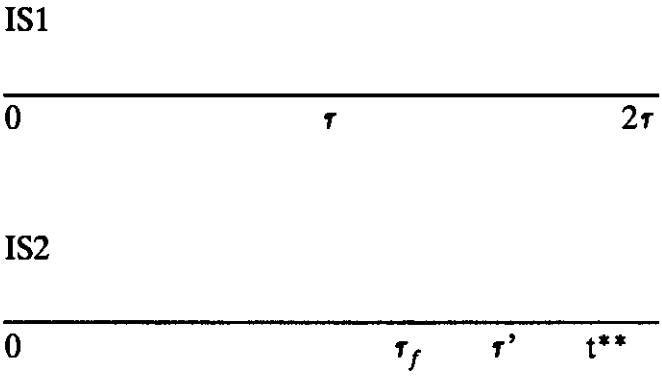

Figure 1. Comparison of Updating Frequency for Two IS

Let $\tau' \leq min\ \{t_1, t_2\}$, where t_1 and t_2 are given by $sup\ \{\theta_f\} = (t_e - t_1)P$ and $A_r(t_2) = k * sup\ \{\theta_f\}$. According to this construction, no action is taken before τ'. Also, let $2\tau > t^{**}$ (as defined in proposition 6). Then the decisions cannot be delayed until 2τ. Since the information on demand for the finished product is updated at τ_f, the raw material information at τ' (which uses the updated information as input) is more accurate than the information at τ. Therefore, the expected cost is lower with the lower updating frequency, $1/\tau'$. •

Discussion: When the two updates occur at the same time for IS1 in Figure 1, i.e., when $\tau = \tau_f$, the signals at τ and τ' will have the same accuracy, and the expected cost with IS1 will not be higher than that with IS2. We also note that the parameters of the two decisions (as reflected in t_1, t_2, and t^{**}) must be considered in determining the optimal updating frequency. For example, with $\tau = \tau_f$ in Figure 1, the two IS will lead to the same expected cost, since $min\ \{t_1, t_2\} \geq \tau'$. As a result, the higher updating frequency of IS1 has no additional value in this example. However, for a situation where $min\ \{t_1, t_2\} < \tau < \tau'$, it is possible that taking decisions at τ (instead of waiting until τ') will lead to lower expected cost.

5. FUTURE RESEARCH

In this paper, we considered a relatively simple, shared information system, and studied its impacts on the performance of a team of decision makers in an inter-related environment. An immediate extension of the present study would involve the generalization of the results to a generic, cooperative decision context. Generalization to decision settings with more than two DMs may also be feasible. More importantly, however, the results derived in the paper highlight several issues which must be resolved for the design of successful organizational computing systems. Future research in this area should include the following topics.

5.1 Transforming Shared IS into Effective Organizational Computing Systems

We showed (among other things) that increasing the accuracy of the IS may have a negative effect on the objective of the team. To that extent, the IS we considered is not an *effective* rganizational computing (OC) system. As emphasized by Applegate et al. (1991), a passive, shared IS, which does not explicitly address the interactions between the decision makers, does not qualify as an OC system. Referring back to the case where DM1 does not have information about a restriction on DM2's action set, a true OC system would possibly incorporate a communication subsystem, which would notify DM1 regarding the actions available to DM2. Several design issues have to be considered in this regard. As an illustration, how frequently should the subsystem update its information and communicate? If communication is costly, then, depending on the sensitivity of DM1's choices to the action set of DM2, an exception reporting scheme may be designed, whereby only certain changes in the action set of DM2 are reported. Such an OC system will not have the limitation of a possible deterioration of performance with improvement in system accuracy. In a more general decision setting, there are additional design considerations. For example, should the subsystem support one-way or two-way communication? Similarly, which DM should initiate the communication under what circumstances? Providing a theoretical basis for transforming simple, shared information systems into effective OC systems for a given set of interacting decisions is an important topic for future research.

5.2 Tradeoffs Between Organizational Parameters and IS Characteristics

Traditional information economics models consider either the decision context or the IS as given, and attempt to find the optimal IS or decision rules respectively. However, in complex decision environments, there may be subtle but important tradeoffs between decision parameters and the IS characteristics. For example, the production rate, P, may be considered as a measure of the organizational slack, and may be treated as an endogenous variable, to be decided in conjunction with the design of the IS itself. With reference to Proposition 4, we note that a higher organizational slack enables the decision makers to utilize a system whose accuracy improves at a slower rate, and still achieves a given performance level, and vice versa. The optimal slack level and the time-variant accuracy of the IS may be determined from a consideration of their relative costs. Such tradeoffs should be considered more explicitly in an extension of the current research.

5.3 Iterative Interactions Between the IS Group and Operational Decision Makers

Traditionally, there has been a communication gap between the developers and end-users of information systems. In the present context, the IS group may be familiar with the technological considerations in the development of the IS, while the end-users may have a deeper understanding of the interaction between the decisions, and the additional requirements it places on the IS to be developed. More importantly, neither the developers nor the users can, on their own, analyze the tradeoffs between organizational and IS issues and select an appropriate design. Therefore, a process of repeated interactions (communication and joint evaluation) between the IS group and the operational decision makers is critical in the design of an effective system (see Balakrishnan and Whinston [1991] for a related discussion on model selection issues). This type of interaction may be modeled as a sequential information gathering and search problem where the developers learn the DMs' requirements gradually and search for a systems solution (see Moore and Whinston [1986, 1987] for a framework on sequential information gathering). An economic model analyzing the interactions and associated information tradeoffs in system design would provide a theoretical basis for a better understanding and management of the development process itself.

6. CONCLUSION

With increasing organizational complexity, there has been a shift of interest towards organizational computing systems, with a view to enhancing coordination, cooperation and communication among multiple decision makers. While there is an emerging body of research on the technical and behavioral issues in organizational computing, the economics of the design of such systems largely remains an unexplored domain of IS research.

In this paper, we adopted an information economics approach to analyze information systems used in making inter-related decisions in a cooperative setting. Using a manufacturing environment as a reference context, we studied the effect of the design of a shared IS on the performance of a two-person team involving a purchasing and a production decision. One significant result of the paper is that when some *relevant* decision parameter(s) of a DM is (are) not known to another DM, a more accurate information system does not guarantee lower cost (or higher payoff, even when the increase in accuracy is obtained for free. Similarly, in an inter-related decision environment, where one DM's action becomes an input to the other's decision, we showed that the optimal partition of the state space for the team is determined only by the action set of the second DM. We investigated some temporal issues in the design of the IS, and obtained lower and upper bounds for the optimal timing of the decisions. The problem of determining an update frequency for the IS in a dynamic environment was addressed. It was shown that a higher frequency may have a negative impact on team performance.

The results of this study highlight some important design considerations for cooperative information systems, such as the role of communication in determining the value of a given IS to the team, the tradeoffs between organizational and IS parameters, and the repeated interactions between the IS group and operational decision makers in selecting design parameters.

7. REFERENCES

Applegate, L. M. "Technology Support for Cooperative Work: A Framework for Studying Introduction and Assimilation in Organizations." *Journal of Organizational Computing*, Volume 1, Number 1, 1991, pp. 11-39.

Applegate, L. M.; Ellis, C.; Holsapple, C. W.; Radermacher, F. J.; and Whinston, A. B. "Organizational Computing: Definitions and Issues," Editorial. *Journal of Organizational Computing*, Volume 1, Number 1, 1991, pp. 1-10.

Balakrishnan, A., and Whinston, A. B. "Information Issues in Model Specification." *Information Systems Research*, forthcoming.

Barron T., and Saharia, A. N. "Optimal Information Structures for the Seller of a Search Good." *Information Systems Research*, Volume 1, Number 2, June 1990, pp. 188-204.

Barua, A. "Three Studies on the Economics of Information Technologies: Assessing Business Value, Strategic Impacts and Information Systems Design." Unpublished Ph.D Dissertation, Graduate School of Industrial Administration, Carnegie Mellon University, Pittsburgh, Pennsylvania, May 1991.

Barua, A.; Kriebel, C. H.; and Mukhopadhyay, T. "MIS and Information Economics: Augmenting Rich Descriptions with Analytical Rigor in Information Systems Design." In J. I. DeGross, J. C. Henderson, and B. R. Konsynski, *Proceedings of the Tenth International Conference on Information Systems*, Boston, December 1989.

Ellis, C.; Gibbs, S.; and Rein, G. "Groupware: Some Issues and Experience." *Communications of the ACM*, Volume 34, Number 1, January 1991, pp. 39-58.

Hilton, R. "The Determinants of Information Value: Synthesizing Some General Results." *Management Science*, Volume 27, Number 1, 1981, pp. 57-64.

Kraemer, K. L., and King, J. L. "Computer-based Systems for Cooperative Work." *Computing Surveys*, Volume 20, June 1988, pp. 115-146.

Marschak, J., and Radner, R. *Economic Theory of Teams*. New Haven, Connecticut: Yale University Press, 1972.

McGuire, C. B. "Comparison of Information Structures." In C. B. McGuire and R. Radner (Eds.), *Decisions and Organization*. Amsterdam: North Holland, 1972.

Mendelson, H., and Saharia, A. "Incomplete Information Costs and Database Design." *ACM Transactions on Database Systems*, Volume 11, Number 2, June 1986, pp. 159-185.

Moore, J., and Whinston, A. B. "A Model of Decision Making with Sequential Information Acquisition (Part 1)." *Decision Support Systems*, Volume 2, 1986, pp. 285-307.

Moore, J., and Whinston, A. B. "A Model of Decision Making with Sequential Information Acquisition (Part 2)." *Decision Support Systems*, Volume 3, 1987, pp. 47-72.

Turoff, M., and Hiltz, S. R. "Computer Support Systems for Group Versus Individual Decisions." *IEEE Transactions on Communication*, Volume 30, Number 1, 1982, pp. 82-91.

Whinston, A. B. "Price Guides in Decentralized Organizations." In W. W. Cooper, H. J. Leavitt, and M. W. Shelly (Eds.), *New Perspectives in Organization Research*. New York: John Wiley and Sons, 1964.

8. ENDNOTES

1. This is always true for the single decision maker case (see Marschak and Radner 1972; Hilton 1981).

2. In information economics models, an information structure is an abstraction of an IS, based on the fineness of the state space partition. However, see Mendelson and Saharia (1986) and Barua, Kriebel and Mukhopadhyay (1989) for multiple attributes of information and their tradeoffs.

3. See Whinston (1964) for an economic analysis of the degree of inter-dependency in decentralized decision making.

4. For example, Proposition 2 relies on the fact that in absence of perfect communication, DM1 is unable to compute the true optimal action for the team. Similarly, the key insight behind Proposition 3 is the concept of action relevance. Neither of the propositions is dependent on the quadratic cost function.

5. More formally, the argument in favor of a decentralized team is based on information and decision costs (see Marschak and Radner 1972). However, without analyzing the tradeoffs between the two structures in this paper, we simply assume the decentralized structure as given.

6. But this does not change DM1's decision rule, since a_r was the best action with respect to the signal that was received at the time of the decision.

7. With perfect communication, for both IS, DM1 orders 99 units when the true state is 99, and nothing otherwise. The corresponding expected cost is

$$\sum_{\theta_f \in \{0, ..., 98\}} \theta_f^2 p(\theta_f) = \$3185.49.$$

8. The same reasoning applies to other elements in the partition.

9. In this paper, we restrict ourselves to decreasing action sets.