

Interaction Value Analysis: When Structured Communication Benefits Organizations

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Abstract

We present a mathematical model that predicts and explains the circumstances under which a management-defined communication structure can add value to an organization. This model provides a game-theoretical basis for contingent organizational design by relating empirical observations of real organizations to the solution of a rational choice model based on game theory. We constructed a multiple-player, noncooperative game in which players have full knowledge of, and universal communication access to, each other. These players allocate the scarce resource of their attention among potential interaction partners. It struck us that this game sometimes did and sometimes did not have a “core,” i.e., a confluence of individual optima (Nash equilibrium) that was also optimal for the whole group. Some circumstances allow the best structure to emerge from many individual decisions, whereas other circumstances require the imposition of structured communication channels by a central decision maker. Strong management control of communication structure adds no value in business environments where the game has a core—i.e., where a centrally imposed optimum would dictate the same communications patterns as those defined by the Nash equilibrium that emerges spontaneously when each participant optimizes locally. Trade in an ideal market is the iconic example of such environments. In our model, other combinations of conditions fail to yield a core, even though a single stable Nash equilibrium always exists. The difference between aggregate effectiveness at the Nash equilibrium and the maximal feasible aggregate effectiveness that could be centrally dictated is the value that management can provide through enforcing the globally optimum communication regime. The predictions of this simple model about the conditions that favor more- or less-structured communications agree surprisingly well with accepted organizational contingency theory. Our simple model thus provides a sound theoretical foundation for many aspects of contingent organizational design.

(Centralization; Communication; Firm Structure; Game Theory; Interaction Value Analysis; Organizational Contingency Theory; Queuing Theory; Social Networks; Welfare Economics)

1. Introduction

Some organizations, such as the military, have always been most effective when their constituent parties adhere to strict guidelines as to how they should communicate with each other. Other organizations tend to thrive better when individuals are free to choose when and with whom to communicate. “Open source” software development, where hundreds of programmers write complex computer programs by collaborating according to individual initiative and interest (Dibona et al. 1999), displays an extreme form of this second, ad hoc, mode of organizational communication.

Thanks in part to improved information and communication technologies, an increasing number of organizations are able to benefit from having fewer controls on their members’ activities (Davidow 1992). We can expect this trend to continue as communication technologies become cheaper, interdependencies become less predictable, and work becomes faster paced.

In this paper, we attempt to answer the question, “Why would organizations choose to respond to different contexts by mandating different degrees of control over who interacts with whom?” We represent an organization as an idealized system of networked rational agents. The agents may be described as “Boulding Level 4” (Scott 1992, pp. 77–81): They modify their behavior to maximize a variable through a simple feedback loop. By statistically analyzing the set of agents and their interactions as a social network (Scott 1991), we are able to show that the value-maximizing communication patterns in that network of simple agents is essentially the same as the communication patterns observed among real human beings in organizations (which is an instance of a Boulding Level 8 system according to Scott).

Our model, which we call interaction value analysis (IVA), focuses exclusively on the value that accrues to an organization from the interactions between the different

parties that constitute the organization. In a real organization, it is almost always necessary to go through a human approver or gatekeeper to gain access to staff, materials, equipment, or capital necessary for accomplishing a work objective. Interaction can thus be used in the model as a stand-in for all work: If the interaction succeeds, the work takes place. This echoes the view developed by Ocasio (1997) that actions are influenced by focus of attention, context, and organizational rules regarding attention, albeit placing it at a higher level of abstraction, i.e., Boulding Level 4 instead of 7 (human intelligence) or 8 (group of humans). Using communication interactions between parties to represent all work lets us use a smaller number of variables to capture the richness of environmental and internal factors that comprise the “context” within which an organization operates. We use five different context dimensions that together dictate the interaction value of any communication pattern in our network model. These dimensions are:

Diversity: the number of independent skill types possessed by parties in the network;

Differentiation: the contrast in skill levels between the most-skilled and least-skilled parties for a given skill type;

Interdependence: the degree to which parties with distinct skills need to collaborate for their individual tasks to be of value to the organization;

Load: the demand for work relative to resources; and

Urgency: the rate at which pending work becomes useless if not completed.

In the IVA model, parties in the organization make decisions about how to allocate their time among different interaction partners. Different interaction patterns allow different levels of interaction effectiveness, as will be explained below. Ideally, all interaction attempts succeed in securing an interaction, and all interactions succeed in adding value to the organization. In practice, because our agents are boundedly rational (March and Simon 1958) and interactions take time, the aggregate interaction value achieved is far less than the potential. Depending on the values of the five dimensions above, a particular time-allocation choice can be found that gives the highest attainable aggregate value of all successful interactions. For the purposes of this investigation, we find this maximum “interaction value” in two different ways:

Global optimum: In an organization with full control of interaction choices: Max(sum(value of interactions attained as a function of the five dimensions, the global interaction value matrix, and the global interaction choice matrix.))

Nash equilibrium: In an organization with no formal control of interaction choices: Sum(max(value of interactions attained by one party as a function of the five dimensions, the global interaction value matrix, and the interaction choices of that party, given that all other parties similarly maximize their own interaction values.))

In the second scenario, each party’s optimal choice of interaction partners is affected by the choices of each other party. The model converges to a Nash equilibrium, defined as a set of choices where no party can improve its maximum without coercing someone else to give up some of its value. The very interesting property of IVA is that, depending on the values of the five context dimensions, the Nash equilibrium may or may not be the same as the global optimum. When the two are equal, the model is similar to classic economic “exchange economy” models (Scarf 1967, Debreu 1959), where a free market is the best way to achieve the greatest good, and governing structures are best utilized only to maintain conditions for a free market (e.g., access to information, common code of conduct). In these cases, we conclude that control of interactions through the organization is not helpful: It may be wasteful of valuable resources and may even be a hindrance when the “central planning” resources are inadequate to locate the global optimum. On the other hand, when the Nash equilibrium gives an aggregate interaction value that is *less* than the optimum, then a legitimate need exists for control of interaction choices. These are the cases where, besides providing the prerequisites for value-adding “transactions,” (Coase 1988, Williamson and Winters 1991), an organization can add value by additionally constraining who interacts with whom.

The idealization that all work consists of interaction allows us to extend the interpretation of our model results from “control of interaction” to “strength of formal or informal governing structure in the organization.” The results of the “IVA” model can now be compared to published studies about the optimal degree of organizational control under different environmental and internal contexts. In particular, we focus on the “organizational consultant” of Burton and Obel (1998), which systematically distilled into about 400 rules the findings of dozens of organizational contingency theory researchers. This literature reports empirical findings about the way that control should be imposed (i.e., the details of structural parameters like formalization, centralization—Mintzberg 1983), as well as about the optimal shape of the network (e.g., span of control, alignment of divisions—Burton and Obel 1980). Details about how and where control is needed are not addressed in our study. Neither do we address the reasons why some interactions are more

desirable than others (Carley 1990), or what the patterns of preference indicate for information transfer efficiency (Burt 1992). Some of these topics may be amenable to examination under the IVA framework, but they are not the topic of the study described in this paper. *The major goal of our research is to demonstrate that the desirability of tighter or looser control of work interactions, regardless of form or mechanism, can be predicted just by considering a confluence of decisions by rational utility-seeking agents about how to allocate their interaction time.*

The remainder of this paper is organized into four sections. Section 2 explains the mechanics of the model we used to derive our results. Section 3 presents our results and illustrates their meaning with several organizational examples. We then compare the results of IVA to contingency theory findings, as catalogued by Burton and Obel (1998) in §4. We conclude with suggestions for further research in §5.

2. Methodology

The basic model of IVA was proposed by Nasrallah and Levitt (2001), based on a social network model initially developed in Huberman and Hogg (1995). Huberman and Hogg investigated the genesis and size of groups within a “community of practice,” defined as a population whose members engage in sporadic, one-way, pair-wise interactions. This idea represents a first step towards providing a contingency theory of the formation of a social network. Huberman and Hogg proposed some simple assumptions about interpersonal interactions and derived an interesting nonlinear relationship between group size, variance in skill level of group members, and the homogeneity of the social network that optimizes the group’s *effectiveness* (F). The basic objective function they used in the maximization is retained in all subsequent versions of IVA. It is:

$$F = \sum_i \sum_j h_{ij} \times p_{ij} \times s_{ij} \quad (1)$$

where

F is the aggregate effectiveness of the organization;

h_{ij} is the value that accrues from an interaction requested by party i and granted by party j ;

p_{ij} is the proportion of party i ’s interaction requests directed at party j ; and

s_{ij} is the probability that an interaction requested by i and granted by j succeeds in realizing its objective.

Given a matrix H of all the interaction values h_{ij} , it is possible to select a matrix P of p_{ij} values that maximizes the objective function (F) while maintaining the

common-sense constraint that all the p_{ij} must be positive numbers that add up to one for every i . The complexity of the optimization depends on how s_{ij} is defined. In Huberman and Hogg (1995), each s_{ij} was a function of p_{ij} alone. In that model, success of any interaction depends only on how often the seeker of that interaction attempts to attain it. By contrast, as will be explained in the sections on urgency and load below, our model introduces a new bounded rationality function for computing the probability of failure. In this new function, it is possible for an interaction seeker i to fail because other seekers after the same interaction partner j make that partner too busy to respond in a timely manner. Mathematically,

$$s_{ij} = s1_{ij} \times s2_{ij} = s1(p_{ij}) \times s2\left(\sum_k p_{kj}\right). \quad (2)$$

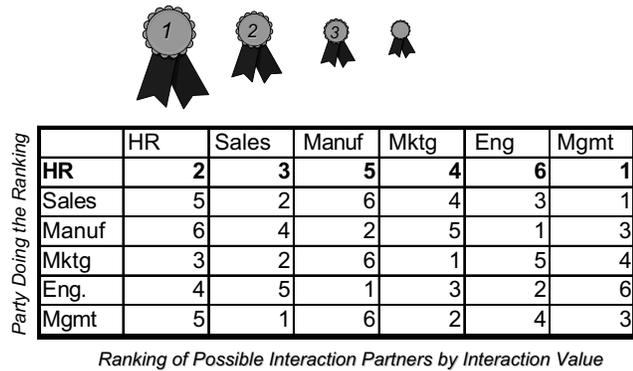
The function $s1$ is the same one used by Huberman and Hogg (1997) as described below under the section on Interdependence. The *new* function $s2$ is also described below under the sections on urgency and load. The basic premise behind the derivation of $s2$ is that interactions that are delayed beyond a threshold time following the initial request *add no value* to the organization. This assumption was successfully tested in the simulation models of the virtual design team (Jin et al. 1996, for example). VDT research (Jin and Levitt 1995, Levitt et al. 1999) operationalized the information-processing view of organizations (Galbraith 1974, 1977). The VDT models have had considerable success in predicting organization failures (Kunz et al. 1998). In IVA, we use a mathematical formulation of the same assumption. The rate of failure $s2$ depends on the parameter for *urgency*, which measures how long it takes on average for an unanswered request to be deemed a failure, and on the parameter for *load*, which influences how long the response is likely to take.

Our use of simple multiplication to aggregate the $s1$ and $s2$ functions is an approximation that neglects dependencies between the two modes of failure. The effects of these interactions were found to be numerically negligible compared to the results, so we used the multiplicative approximation.

2.1. Definitions of Context Parameters

2.1.1. Diversity. The first step in building an IVA model is to have each party in the organization rank every other party in order of how much value they expect to derive from an average interaction with a member of the other party. Figure 1 provides an example of how a six-party organization might perform such rankings.

Figure 1 A Ranking Matrix for a Six-Party Organization



More generally, the matrix in Figure 1 represents an organization where any six classes of people classify the same six classes. (Note that interactions within the same class—e.g., asking questions of someone in your own department or profession—are treated no differently from interactions with another class.)

All the rows in Figure 1 are linearly independent. Having linearly independent rows indicates that we have selected the number and composition of the parties in the model so as to obtain the right size of matrix for what we call the diversity of the organization.

We expect the diversity number to be much smaller than the number of individuals in the organization. Similar rankings are given by different people even when there is no clear compartmentalization of the people doing the ranking (as possibly suggested by our choice of party names in this example). This is because people have common needs and values. This nonindependence is revealed when some individuals, whom we call “popular” individuals, receive the highest possible ranking, i.e., the “top” ranking, from a large number of their peers. A combinatorial study of how one could become the “most-popular” individual out of a group performing *statistically independent* ratings shows that in most cases, a “most-popular” individual would emerge with surprisingly few “top” rankings (Nasrallah et al. 1998). For example, in a random ranking exercise, groups of three to eight parties would be most likely to give no more than two top rankings to any member. The larger the group of independent rankers, the smaller the fraction of top rankings for the same individual needed to make that individual the “most popular” in the group: With 3–8 statistically independent rankers, having a maximum score from just two rankers suffices to make a person the most-popular interaction partner; with 9–90 statistically independent rankers, one needs a maximal score by 3 rankers to become most popular; and with

5 billion statistically independent rankers, the most popular person needs only to have a maximal score by 7 rankers.

Because we expect organizations to have popular individuals who garner more than such a small number of top rankings, it follows that the matrix whose cardinality is the number of individual organization members will not have linearly independent rows. In linear algebra, this means that the matrix is degenerate and cannot be inverted. For this reason, we prefer to work with a reduced matrix where the rows indicate ranking *criteria* that several individuals may use to rate other individuals. For business applications, this can represent independent skill types possessed by individuals that are necessary for carrying out the work. Every individual has a proficiency rating according to each criterion (i.e., in each skill type), so the larger individual-to-individual ranking matrix can be reconstructed from the criterion-to-criterion matrix if we still have a record of how each person (a) uses and (b) is proficient at each skill. Full linear algebraic details are given in Nasrallah et al. (1998).

Ranking criteria are not equally weighted in real situations. Some skills may be used by a large proportion of the organization for ranking interaction partners. Others may be of interest to only one or two parties. Using an example where the criteria are weighted equally is an *idealization* that allows us to represent diversity as a single number instead of a distribution across the $N \times N$ ranking space. Under this idealization, the ranking matrix in Figure 1 represents six equally weighted criteria. Any organization whose parties rank one another such that one party obtains one-third of the top rankings may be represented by this idealized 6×6 matrix. In the rest of this paper, Figure 1 is used to generate the model results for the “medium diversity” examples. The organization is somewhat diverse because no one is preferred by more than one-third of the parties. In contrast, the “low diversity” results are obtained from a 3×3 matrix where one column contains two ones (top rankings). Two-thirds of the members share the same top preference. The actual numbers selected (one-third and two-thirds) are clearly arbitrary, but they are sufficient to illustrate the trend created by the diversity parameter.

What effect should we expect diversity to have on knowledge-transfer effectiveness? People who receive a larger number of interaction requests will have a harder time responding to those requests under assumptions of “bounded rationality” (March and Simon 1958). Someone whose favorite interaction partner is one of these “popular” individuals would find it more effective to seek interactions with less-popular individuals to minimize the chances of being overlooked. It is precisely

the competition for popular individuals that makes the time-allocation exercise into a nontrivial game. This justifies our election to focus on cases where there are three to six criteria. Additional independent criteria will tend to reduce the popularity of the most-popular individual (thus their scarcity) and hence will reduce the need for a controlling structure to ensure optimal distribution of communication.

2.1.2. Differentiation. Given a ranking matrix of the appropriate cardinality, we now need to translate these ordinal rankings into real numbers. Doing so enables us to make comparisons between the value of an interaction with a higher-ranked partner and the value of an interaction with a lower-ranked partner. We define *differentiation* as the ratio of the value of interacting with the favorite versus the value of interacting with the least favorite. This particular definition makes it possible to ignore the effect of organization size on the results of the model. Because we are dealing with an idealization and not with a real organization, we impose homogeneity along two dimensions. First, we assume that each step down the list of rankings reduces value by the same ratio. This means that the sorted list of values is a geometric progression. Second, we assume that differentiation is homogeneous across the organization’s parties, so all parties have the same differentiation ratio. This means that all the rows in the value matrix are permutations of the same list of values. The ranking matrix in Figure 1 thus becomes a matrix of interaction values, as shown in Figure 2, for a differentiation level of 10. For each row, representing an interaction seeker, the lowest-ranked partner has a value of 1, the highest-ranked partner has a value of 10 (i.e., the diversity value), and all the other values are calculated to give a geometric series linking the two.

$$h_{ij} = \text{Differentiation}^{((\text{Diversity} - (\text{ranking of } j \text{ by } i)) / (\text{Diversity} - 1))}. \tag{3}$$

High differentiation means that interacting with the most proficient (i.e., highly ranked) partner in a skill (i.e., ranking criterion) yields much more value than interact-

ing with someone with a lower ranking. Low differentiation makes it more acceptable to settle for a partner with a lower ranking, so competition for high performers is less acute.

2.1.3. Interdependence. Huberman and Hogg (1995) introduced “hint production period” as the average amount of time that must elapse between successive interactions with the same member of your “community of practice” for that member to have gathered enough insight to be of help again. In the context of an organization, there is also an ideal average wait time between interactions with the same organization member. For example, some work tasks may need to be completed by the requesting party (or by the responding party) involving different third parties to prepare the way for a specific information exchange to be of value to the organization. In IVA, we aggregate the effects of those different requirements and simply use an ideal average rate of interaction. The same mathematics used by Huberman and Hogg (1995) to describe a “community of practice” can thus be applied to describe the amount of overall interaction time that must elapse before a subsequent interaction with the same person can be useful. During this time, some average number of interactions may occur between any given pair of parties. The number of interactions that are enablers to the particular interaction in question may vary in reality, but we again idealize by assuming that the rate at which these salient interactions occur is proportional to the overall interaction rate and, therefore, to the elapsed time as well.

We interpret this proportionality constant in IVA as the degree of task interdependence. When there are many interdependencies in the work, then more attention must be paid to related tasks before any specific interaction can once again yield value. When most tasks are *not* dependent on many others, then it becomes possible to focus on a single task, and therefore to interact with the same partner at a higher rate.

To normalize interdependence for organization size, we express it as the fraction of the population that must be interacted with between successive interactions with a specific person (Nasrallah and Levitt 2001). The exact function used for $s1_{ij}$ in Equation (2) is given below as Equation (4):

$$P[\text{Interaction adds value}] = s1_{ij} = \frac{1}{1 + (p_{ij} \times \text{Interdependence} \times \text{Diversity})}. \tag{4}$$

The parameter interdependence is a dimensionless ratio of two rates for two stochastic processes, one that generates interactions between *i* and *j*, and one that generates interactions in general. The whole function $s1$ is also

Figure 2 Interaction Value (H) Matrix for Diversity = 6 and Differentiation = 10

	HR	Sales	Manuf	Mktg	Eng	Mgmt
HR	6.3	4.0	1.6	2.5	1.0	10
Sales	1.6	6.3	1.0	2.5	4.0	10
Manuf	1.0	2.5	6.3	1.6	10	4.0
Mktg	4.0	6.3	1.0	10	1.6	2.5
Eng	2.5	1.6	10	4.0	6.3	1.0
Mgmt	1.6	10	1.0	6.3	2.5	4.0

dimensionless because p_{ij} is a dimensionless fraction of interaction attempts.

2.1.4. Load and Urgency. The effect of interdependence as defined above is to induce parties to seek interactions with a collection of partners instead of with a single preferred partner. Nevertheless, popular individuals may still become targets of more requests for interaction than they can handle. In other words, the most useful people in the organization will have a queue for their attention, which may reduce their overall usefulness as a source. How does this translate to reduced effectiveness? We use a simple representation originally operationalized in an organizational context by Levitt et al. (1999), and inspired by Mintzberg (1983) and Galbraith (1977). A party that attempts to communicate with a busy potential partner is simply assumed to give up the attempt after a certain threshold wait period. A request arrives in a person’s in-tray and, depending on how busy the person is, the request may get processed while the requester still needs it, or it may stay in the in-tray until responding to it no longer adds value. Mathematically, this is a “queue with renegeing,” first solved by Barrer (1957). In IVA we recognize that many independent factors may lead to a request being generated, being superseded, or being successfully responded to. All three types of events are thus equally random. Mathematically, we can assume exponentially distributed interevent times for each of these three types of events, which leads us to a memoryless system with three random processes. We also assume the busy person will act in a fair manner and respond to requests on a first-come, first-served basis. Finally, we define the queue to allow a request to become obsolete even after the responding party has started processing the request. With these assumptions, the only variables that affect success rate are the ratios between the rates of these three processes. The new dimensionless parameters thus introduced are:

$$\text{Load} = (\text{Average number of requests from one party per unit time}) / (\text{Average number of responses by one party per unit time});$$

$$\text{Urgency} = (\text{Average number of time-outs per request per unit time}) / (\text{Average number of responses by one party per unit time}).$$

“Load” is the ratio of arrival rate over service rate for interaction requests. This represents how much work an organization has relative to its resources. The concept is familiar from standard queuing theory, where it is called the “server utilization rate” or “arrival/service ratio,” and denoted with the Greek letter ρ (rho). Because we have several parties submitting requests to

each of a number of queues, the ρ for each queue is obtained by multiplying the organization’s load parameter (defined above) by the sum of the responding party’s column in the time-allocation matrix (P). When someone has two as the column sum, for example, then that person gets the equivalent of two full-time people’s requests.

“Urgency” represents how quickly people demand responses to their requests. It is not the same as load, although growth in a company’s transaction volume will tend to affect both. For example, a recently funded Internet start-up in 1998 might have low load and high urgency because the funding attracts a large number of employees and other resources, but the rush to ship product and grab market share makes it necessary to speed up all decisions. If the money comes close to running out, load becomes high too because management is reluctant to hire more people to keep up with workload. After the company starts trading publicly and things are more stable, urgency will be lower but load will remain high because scrutiny of public investors may cause management to be more scrupulous about hiring more people.

The mathematical formulation of a queue where the queuing parties renege at random (instead of after a fixed time) was first worked out by Ancker and Gafarian (1962). Figure 3 shows the state transitions that are possible in this queuing system, and can be used to gain an appreciation for its dynamics and for the first steps in the derivation of the solution. The success function s_2 that we seek for Equation (2) is the fraction of parties that remain in the queue long enough to be served, which is given by the Equation (5) below.

$$s_{2,ij}(\text{Load}, \text{Urgency}) = \frac{G\left(\frac{\text{Load}}{\text{Urgency}} \times \sum_{i=1}^n p_{ij}, 1 + \frac{1}{\text{Urgency}}\right)}{\text{Load} \times \sum_{i=1}^n p_{ij} \times G\left(\frac{\text{Load}}{\text{Urgency}} \times \sum_{i=1}^n p_{ij}, \frac{1}{\text{Urgency}}\right)} \tag{5}$$

The function G stands for the cumulative gamma distribution, which is defined as:

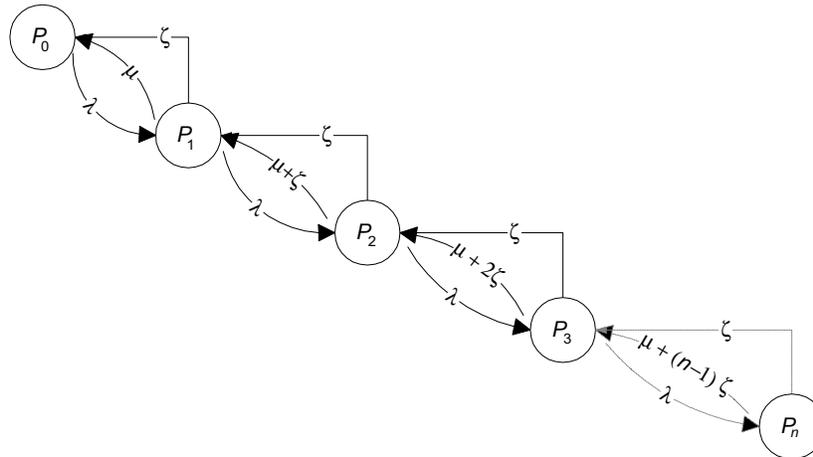
$$G(x, \alpha) = \int_0^x \frac{x^{(\alpha-1)} e^{-x}}{\Gamma(\alpha)} dx. \tag{6}$$

G is one of many ways of expressing the incomplete gamma function $\gamma(x, a)$ (Pearson 1983) and we used it here for compatibility with our numerical solution software.

2.2. Optimality with Infinite Capacity

It is relatively straightforward to find one’s optimum allocation of time among interaction partners when the

Figure 3 Markov Chain for Queue with Randomly Reneging Parties



only constraint on how often one can go to one’s favorite is derived from interdependence. This is the “inessential” game model, where the success of one player s_{ij} only depends on the frequency of that player’s interactions. Deviating from the optimal allocation, either up or down, leads to a reduction in individual effectiveness but has no effect on others’ effectiveness. Global effectiveness is reduced by exactly the sum of individuals’ reductions. This means that if every party is left to optimize its behavior, then it trivially follows that the behavior of the organization as a whole will also be optimal. No management oversight of interaction-request frequencies is necessary for this inessential case.

In real life, low-intensity contacts whose frequency never increases beyond a trivial level (e.g., diffuse communities of practice) do not need a management structure at all.

2.3. Introducing Bounded Rationality

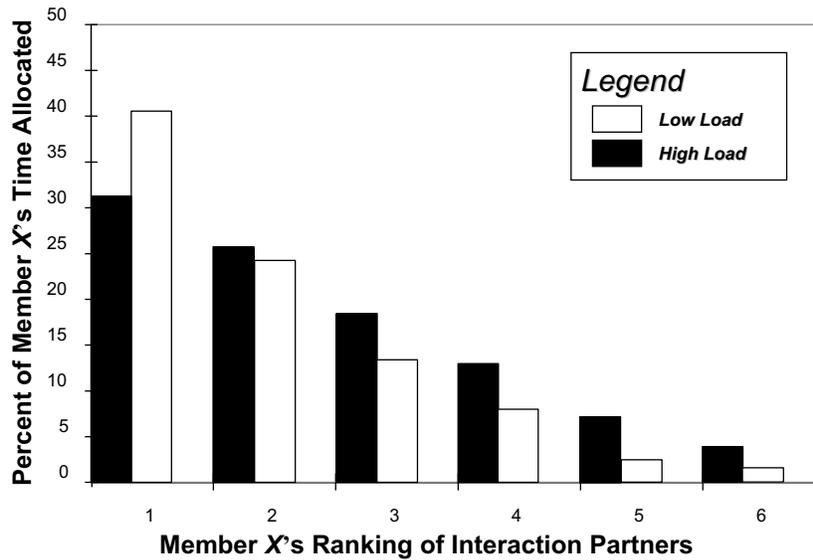
When we consider the effect of resource constraints arbitrated by impatient queuing within the interaction value framework, the expression for organizational effectiveness becomes more complicated. We need to substitute Equations (2), (3), (4), and (5) into Equation (1) to obtain:

$$\begin{aligned}
 F &= \sum_{i=1, j=1}^{\text{Diversity}} p_{ij} \times h_{ij} \times s1_{ij} \times s2_{ij} \\
 &= \sum_{i=1, j=1}^{\text{Diversity}} p_{ij} \\
 &\quad \times \text{Differentiation}^{((\text{Diversity} - (\text{ranking of } j \text{ by } i)) / (\text{Diversity} - 1))}
 \end{aligned}$$

$$\begin{aligned}
 &\times \frac{1}{1 + (p_{ij} \times \text{Interdependence} \times \text{Diversity})} \\
 &\times \text{Load} \times \sum_{k=1}^{\text{Diversity}} p_{kj} \\
 &\times G\left(\frac{\text{Load}}{\text{Urgency}} \times \sum_{k=1}^{\text{Diversity}} p_{kj}, \frac{1}{\text{Urgency}}\right) \\
 &\times G\left(\frac{\text{load}}{\text{Urgency}} \times \sum_{k=1}^n p_{kj}, \frac{1}{\text{Urgency}} + 1\right) \tag{7}
 \end{aligned}$$

This function has the precise property that we are seeking. Even though the effects of each party’s behavior may be felt by other parties, allowing each party to selfishly optimize the effectiveness of its interaction requests *sometimes* results in optimum effectiveness for the whole organization. In the language of game theory, we have an “essential game” situation where a “core solution” *may or may not* exist depending on the values of the parameters (load, urgency, interdependence, differentiation, and diversity). When a core solution exists, allowing all the parties to react to one another’s optimizations until none can make any further improvements (i.e., until a Nash equilibrium is reached) gives a time allocation (P matrix) that is optimal for the whole organization. When a core does not exist, there is *still* a Nash equilibrium that all the parties always reach as a result of reacting to each others’ local optimizations. However, the total organizational effectiveness under this equilibrium is lower than the effectiveness that can be obtained under a globally optimized (i.e., centrally mandated) communication structure. We illustrate these different optima using Figures 4 and 5. These depict the model output for two slightly different contexts with a

Figure 4 Sample Time Allocations Among Interaction Partners

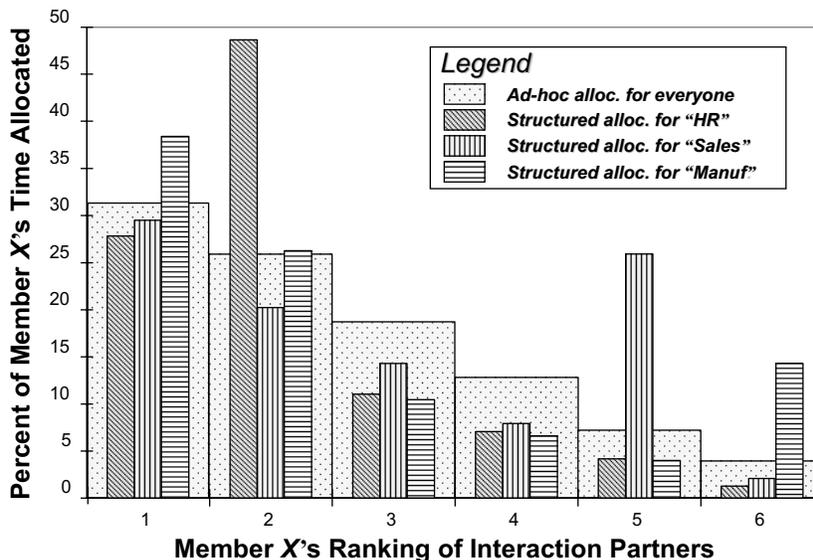


diversity level of 6. The bars show how a typical member of that organization might optimally allocate his or her time among the six choices.

In Figure 4, the Nash equilibrium time-allocation distribution was found to be identical for all parties when plotted against their ranking of interaction partners. Although each party may have a different favorite, the amount of time spent attempting to interact with one's favorite is identical for all parties under the Nash equilibrium. The two distributions contrasted in Figure 4 represent the Nash equilibrium solutions for these

parties in two different contexts with differing values for the "load" parameter. However, in some contexts, the locally optimized Nash equilibrium allocation of communication time for these parties will be different—and potentially less valuable to the overall organization—than the globally optimum time allocations for the parties. Figure 5 depicts one such context. The six wide bars in Figure 5 represent the Nash equilibrium distribution identical to the "high-load" distribution in Figure 4. In this case, to achieve the highest possible sum of interaction values for the organization, it is necessary to impose

Figure 5 Sample Time Allocation Demanded by Formal Structure



significant and nonobvious changes in time allocations from the locally optimized Nash equilibrium behavior for the parties. The thin bars of Figure 5 provide details of the required set of deviations for three of the parties whose interaction partner rankings and interaction values appear in Figures 1 and 2, respectively. The allocations for this example were calculated using medium settings for load, urgency, and interdependence. The global optimum follows from having the “HR” party (represented by the diagonally hatched bars in each series) allocate much more (50% vs. 27%) of its time to its second favorite and somewhat less (27% vs. 32%) to its top favorite, (etc., as shown).

The second party, “sales” (represented by the vertically hatched bars) allocates slightly less time than the Nash equilibrium amount to its favorite and much more time to its fifth favorite. The need to enforce these deviations from locally preferred time allocations of the parties is synonymous in IVA with the need for some sort of management structure that channels interaction-request frequencies towards the global optimum.

A review of Figure 1 reveals the one distinction between different parties in the organization that is permitted in this otherwise homogeneous model: popularity. What distinguishes the first two parties from the third is that the first two both vie for the same favorite (see Figure 2). The party denoted as “management” is therefore the most popular. Both of the parties whose favorite is the popular “management” must make greater reductions in their use of that favorite when moving from the Nash equilibrium to the global optimum. Other parties in this example have to make less of an adjustment when making the same transition. Note also that “HR” has a second-favorite who is not any other party’s favorite. “HR” does no harm to the organization if it only interacts with that second favorite interaction partner (incidentally itself) as much as 50% of the time, as shown in the previous slide. In contrast, “sales” has to go all the way down to its *fifth* favorite before finding a party that is not anyone’s favorite. That fifth favorite, “HR,” is the partner with whom “sales” can spend all the time left over because “management” is a popular interaction partner and cannot fulfill all of “sales’s” requests for face time. The third player, personifying “manufacturing,” has a favorite, “engineering,” who is not the favorite of anyone else. “Manufacturing” thus gets to allocate its time in a pretty regular diminishing curve until it gets to the least popular, and hence most free, “HR” party. “HR” gets more of “manufacturing’s” requests than the more preferred “sales,” “marketing,” and “management” partners, because they are relatively more popular and thus available less often.

2.4. Generating Numerical Results

As a result of all this micro-behavior, a series of trends emerges in the variance between the two optima as plotted against the five parameters. We represented Equation (7) in a set of spreadsheets in Version 7.0a of Microsoft Excel, (© 1985–1996, Microsoft Corporation). The two different optima were then obtained by numerical optimization techniques as implemented in the “solver” add-in of that software package. We imposed two sets of constraints: that proportions of one’s time cannot be negative and that the sum of all those proportions must add up to one. We used these worksheets to perform numerical optimizations for various values of the parameters. The global optimum followed from a single run of the solver. The Nash equilibrium was obtained by repeatedly cycling through the individual parties’ optimizations until none of the parties’ optimal values were increasing by more than 1/100,000. This numerical solution method gives no mathematical guarantee that the equilibrium is unique or global, so we had to check our results by repeating the process from different initial points (i.e., different P matrices). Our search did not yield any instances of multiple points of convergence. Knowing when and why the Nash equilibrium is unique is, of course, an interesting research topic in and of itself, and we leave this for future research. For each combination of parameter values, we next determined what fraction of the globally optimum effectiveness is lost when we use the Nash equilibrium of individual party optima. This percentage reduction from the globally optimum effectiveness represents the maximum value that a managerially imposed communications structure can add. When the value gap is near zero, absence of a management structure does little harm. When the value gap is relatively large, a management structure can increase effectiveness by enforcing communication patterns that individuals would not choose independently. The percent difference in aggregate value or “organization effectiveness” (F) between the formal vs. the ad hoc communications structure is our dependent or “output” variable. We denote this variable by the term “value of structure” and plot it on several charts against the values of the five parameters that go into Equation (6).

Because we have five input parameters vs. one output variable, we used three-dimensional plots with different pairs of the five input parameters on the x and y axes, and the output on the z axis. For each such plot, the three input parameters that are not shown on the axes are controlled for—i.e., they are set at a fixed value that represents a specific organizational situation. These values are displayed in the top right corner of the graphs. The

Table 1 Values of Parameters Used in Examples

Parameter	Low	Medium	High	Max
Diversity	3 parties	6 parties		
Differentiation	1.5	31.5	92	107
Interdependence	1	3	7	9
Load	0.15	0.3	0.91	0.99
Urgency	0.05	0.33	2	2

numerical values corresponding to ordinal values (high, medium, low) of the input variables are given in Table 1.

3. Results

We chose four example scenarios to illustrate how one might interpret the model results.

3.1. Illustration 1: Military Under Different Loads

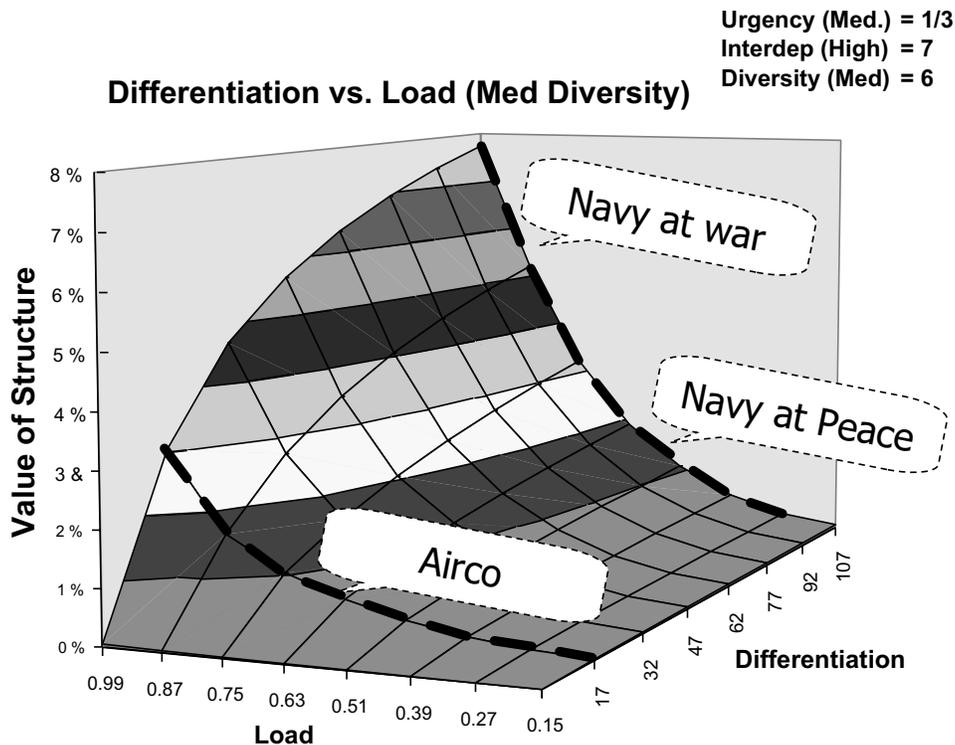
The background for this military example was obtained from interviewing a former U.S. Navy officer from the Construction Battalion (the “Seabees”). She explained that the degree of bureaucratic structure inherent in all operations was often much higher than what would have been indicated by common sense. The cost of the bureaucracy was deemed higher than its benefit during

normal peacetime construction projects. The rationale for the “Seabees” nevertheless having a high level of structure is that Seabee construction projects will occasionally have to be carried out under battle conditions, which do not obtain most of the time.

To illustrate how the interaction value model accounts for this distinction, we plot the value of structure against differentiation and load. High differentiation is what characterizes military organizations because they mobilize large numbers of individuals with a wide range of education and experience—i.e., a high variation in skill levels. Time of battle equals high load, as that is where combatants are called upon to respond rapidly to interaction requests to the limit of their capacity. The upper, bold, dashed line in Figure 6 shows how a military organization goes back and forth on the load scale, while maintaining the same differentiated mix of individuals. The high end of the curve justifies the need for high-interaction-governing structure at all times because it is not possible to fine-tune a response to battle conditions by adding and removing the habits and regulations that constitute communication structure in the military.

Contrast this to “Airco,” a commercial airline with mostly college-educated professionals, thus having a

Figure 6 Value of Structure for “Military” Example



lower level of differentiation. The lower, bold, dashed line in Figure 6 shows that because the sensitivity to load is not as high, it is possible to get by with a level of structure that is not too far from the ideal under average load conditions. This is why one is less likely to hear complaints about stifling bureaucracy in an organization such as a commercial airline where differentiation is lower and load is never as high (even in the worst Christmas snowstorm) as it is for an army in a raging battle to secure a beachhead.

Figure 7 shows that reducing diversity to a value of 3 (independent, equally weighted selection criteria) has no effect on the overall shapes of the curves. The only change is that the value of structure at maximal differentiation and load goes up from 8% to 11% of the organization's productivity. We can relate this to the real-world example of a military organization in historical times. Although the armies of Julius Caesar, for example, were arguably as differentiated in terms of skill level as today's military, there were fewer distinct skill sets available in those times. This meant that a rigid command structure was even more important than it is now in keeping the organization functioning during the high-load times of war. In contrast, an organization like Plato's Academy, with less differentiation in the same society (interpreted as the same diversity level), had less need of structure than its military counterpart when faced with taxing work loads. Across societies, we see that the value of structure

at high load in the Academy (6%) is higher than in Airco (3%) because the diversity in ancient times was lower. This is despite the observation that during low-load periods, the value of structure may have seemed as low in all instances: The military organization with its high differentiation, the civilian one with its low differentiation, ancient society with its low diversity, and modern society with its high diversity. Structure can add value, and thus be cost-effective, when the ability to respond to high-load needs is important to the success of the organization in all but the modern, civilian organization.

3.2. Illustration 2: Open-Source Development Under Different Urgency Requirements

This example was provided by an interview with developer Sam Ockman (Dibona et al. 1999). His experience with developing operating system software under the open-source paradigm indicated that he sometimes had to develop certain modules under tight time constraints. These conditions did reduce the effectiveness of the unstructured support network that characterizes the open-source community.

The explanation for this phenomenon is the uniformly high level of competence necessary for participation in open-source development. It takes a high level of technical expertise to even contemplate contributing to an open-source project, and it takes even higher expertise to be recognized by others as a member of the devel-

Figure 7 "Ancient Military" Example

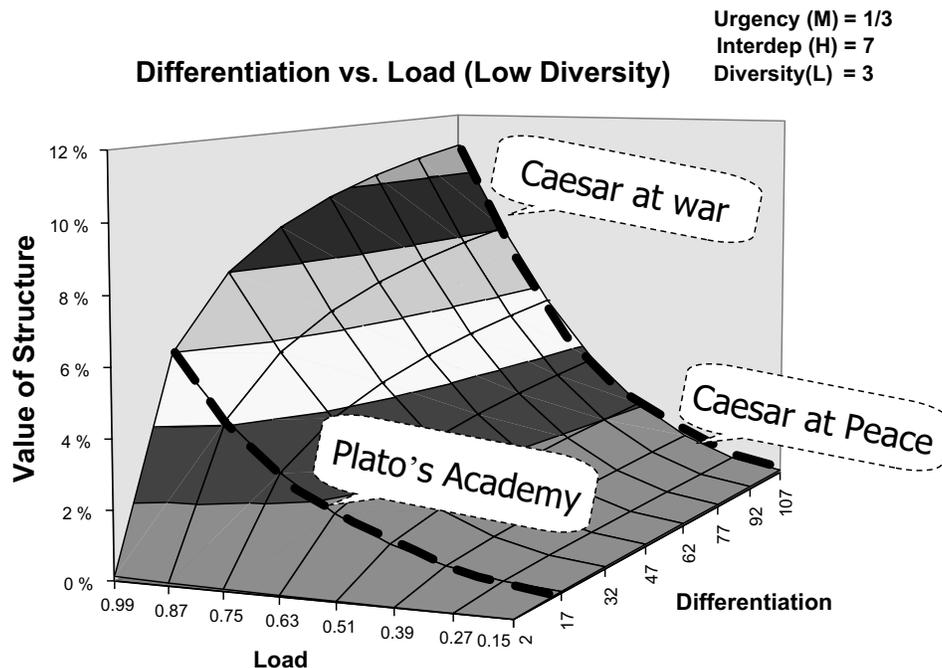
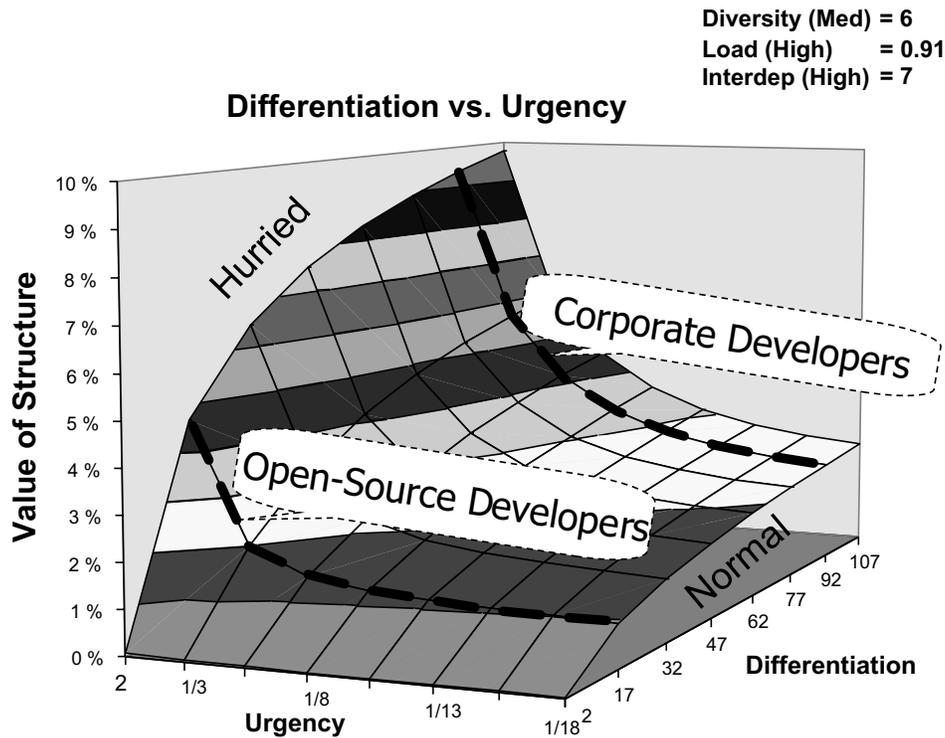


Figure 8 Value of Structure for “Open-Source” Example



oper community. The lower, bold, dashed line in Figure 8 shows that an impatient individual can still receive good support in less-differentiated organizations performing highly interdependent tasks. As long as the urgency is not very high, no communication structure is needed to constrain people to share information with specific interaction partners. The value of structure remains almost as low for teams with moderate levels of urgency as for teams that can afford to wait longer for responses. In contrast, a commercial-development environment has less-experienced programmers interspersed with experts, so its differentiation level is higher. In that environment, structure becomes valuable when urgent deadlines loom, and people cannot wait for answers. This is illustrated by the upper, bold, dashed line in Figure 8.

3.3. Illustration 3: Large Software Company for Varying Interdependence

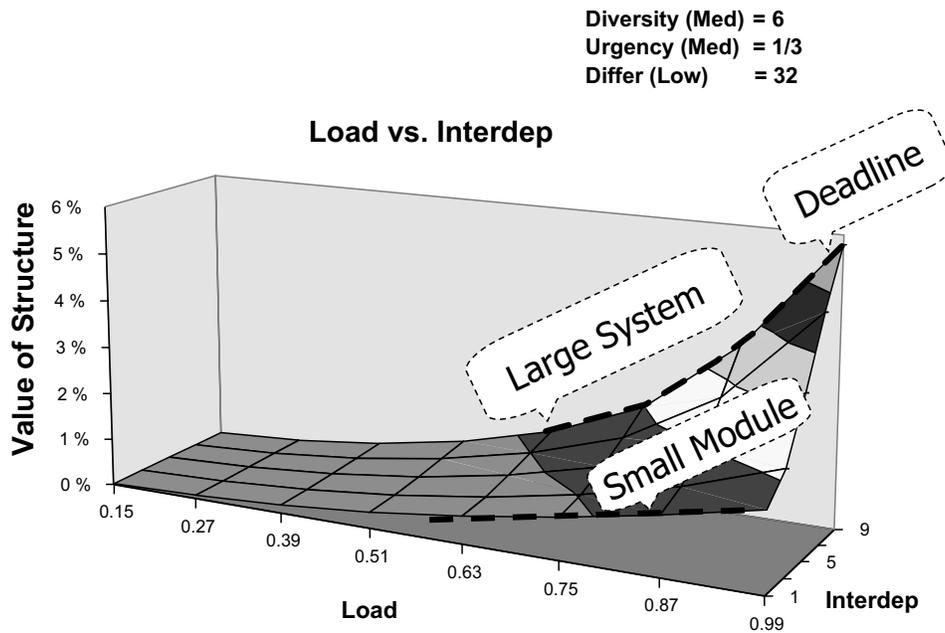
In contrast to open-source development, the first author’s experience in a corporate software-development environment led to the following example. We observed that the workload increases close to the code-freeze dates. At those times, management exercises tighter control by more frequent meetings at the level of the product as a whole. The small teams, working on the

autonomous modules, continue to operate under looser control by their team leaders. The different amount of reliance on a communication structure between the two scales is explained by variations in interdependence. Figure 9 shows that when interdependence is low, load does not predispose the organization towards tighter structure (lower, bold, dashed line). In real life, a programmer working on a small module with well-defined interfaces is not dependent on other programmers for day-to-day interactions, and hence can work harder to meet a deadline without much interference from his manager. When interdependence is higher, e.g., for interactions between user interface and functional design, then as deadlines approach the graphic designers and product managers in charge of those features need to spend more and more time in meetings mandated (and often attended) by higher management. This is because structure becomes more valuable as deadlines push the load higher (upper, bold, dashed line).

3.4. Illustration 4: Health-Care Organization at Varying Diversity

The final illustration in this series comes from accounts in the popular press about the failings of, and resistance by physicians and patients to, health-maintenance organizations (HMOs). Attempts to impose a tight rein on

Figure 9 Value of Structure for “Corporate Software” Example



medical practice lead to many problems. For instance, the San Francisco Chronicle reported in December 1999 that health-insurance purchasers derived lower costs from looser cooperatives of individual medical practitioners than from traditional HMOs. We explain this from an interaction value perspective by noting that most of the work of doctors treating different patients is not very interdependent. Every patient is different, and differences are primarily addressed locally. The lower, bold, dashed line in Figure 10 shows that the value of structure is minimal, and usually not worth the cost. This is regardless of whether differentiation is high, as in a hospital with many levels of doctors, interns, nurses, and orderlies, or low, as in a clinic with several doctors sharing support staff. Only when interdependence is high and differentiation is medium to high does it begin to pay to manage people’s interactions. Examples of such a case would be a team of volunteers assisting in controlling an epidemic or responding to a natural disaster or an act of war, as shown by the upper, bold, dashed line in Figure 10.

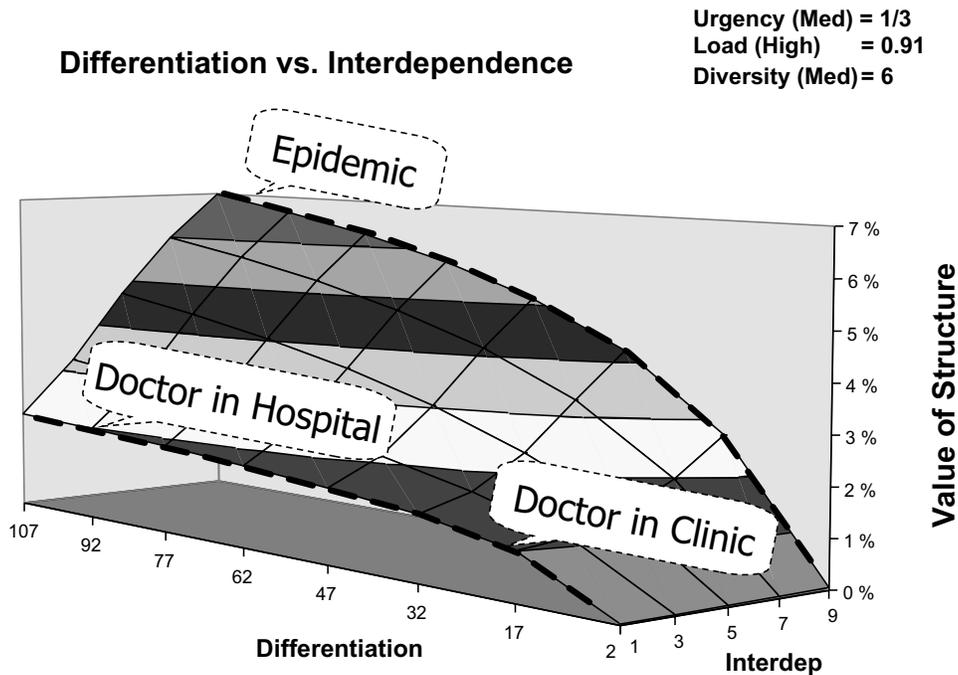
3.5. General Observations

We can generalize from the examples above to say that structure adds value to organizations when: Diversity is low to medium, interdependence is medium to high, differentiation is medium to high, urgency is medium to high, and load is high. Conversely, the value added by an imposed structure will be *low* when diversity is high, or any of the other parameters is low, or load is medium.

The need for all the parameters to be near the appropriate end of their scale demonstrates why models that do not account for all the elements in IVA might have failed to exhibit a similar match with organizational contingency theory.

It remains to map the parameters defined within the model to the types of measures that field researchers use to characterize organizations and business environments. Diversity is the parameter that represents the complexity of environment and technology. More complexity means more criteria for ranking interaction partners, hence less chance of bottlenecks and less value from regulating interactions. Differentiation correlates inversely to the pervasiveness of uniformly trained individuals. A high degree of professionalization makes the differentiation parameter low (because the distinction between the highest and the lowest is less). Low differentiation lowers the value of structured communication vis à vis an ad hoc mode of organization. High load combined with high urgency corresponds loosely to a hostile environment; more of both would favor management structure. Urgency influences overall effectiveness in the same direction as high load (March and Simon 1958), but it does not favor structure as much as load does. This explains why fast-moving companies in the high-tech area tend to place so little value on restrictive management structures. Information in the high-tech world becomes outdated much more quickly than in the traditional company. High-tech companies are thus inher-

Figure 10 Value of Structure for “Health-Care” Example



ently unable to use communication structure to improve information-exchange efficiency, unlike more traditional companies that suffer more from load than from urgency.

4. Conclusions

Many researchers in the organizational contingency theory literature have observed how different types of competitive and technological conditions give one form of organization an advantage over another (Galbraith 1977, Mintzberg 1983, Scott 1992). Burton and Obel (1998) surveyed and compiled this literature and derived general heuristics for diagnosing and designing organizations to fit their contexts. IVA contributes to organization contingency theory by proposing a fundamental mechanism that leads from those observed general conditions to the observed outcome. The causal relationship is derived from a model of rational choice instead of being associative or heuristic. The parameters that we use in IVA also have the advantage of being relatively objective measures, upon which independent observers can more easily agree. Table 2 below maps our results to the findings of organization contingency theory.

IVA can be seen to subsume some, but not all, previously published rules of thumb for organizations. For example, IVA does not have anything to say about power, media richness, or divisional form. IVA’s “higher value of structured communication” sometimes maps to

“high formalization,” sometimes to “not ad hoc form” and sometimes to “high centralization.” However, IVA’s strength is that, unlike the disparate rules above, it links the different parameters under a common framework. This allows us to model and analyze the interplay among different factors that affect the value of structured communication in organizations. More significantly, IVA demonstrates that, in those cases where it has something to say, a simple model suffices to emulate the properties of more complex entities, namely organizations.

5. Next Steps

We demonstrated the model’s potential in the Results section above by obtaining general predictions about specific industry situations. Those situations were described using specific, objectively measurable parameters that were treated as homogeneous across the population of an idealized organization. This is only the beginning. With additional calibration and validation, IVA may help to further investigate, articulate, and elaborate current knowledge about the theory of organizations. This requires field research for “calibration” of the IVA model before it can be used to give specific recommendations to an organization facing a specific situation. On the theoretical side, many questions remain open about how the model’s properties come about and what the minimal requirements are for a model to have

Table 2 Structural Propositions from Two Leading Contingency Theory Organization Design Texts vs. Predictions of IVA

Mintzberg	Burton and Obel	Interaction Value Analysis
"Extreme hostility in its environment drives any organization to centralize its structure temporarily" (Mintzberg 1983, p. 141, Hypothesis 12).	Hostile environment: "If hostility is extreme, then [...] centralization should be very high" (Burton and Obel 1998, p. 184, Proposition 6.9).	High load and urgency imputes a higher value to structure. These conditions together are typically found in organizations under threat.
"The larger the organization, the more elaborate its structure—i.e., the more specialized its tasks, the more differentiated its units, and the more developed its administrative component" (Mintzberg 1983, p. 124, Hypothesis 3).	"If the organization is large, then formalization should be high" (Burton and Obel 1998, p. 158, Proposition 5.12).	Higher load and interdependence impute a higher value to structure. This combination is typically found in larger, well-established organizations.
"The adhocracy must hire and give power to experts—professionals whose knowledge and skills have been highly developed in training programs" (Mintzberg 1983, p. 255).	High professionalization leads to low or medium formalization within units (Burton and Obel 1998, p. 158, Propositions 5.13 and 5.14). If the organization is small, then formalization should be low and configuration should be simple or ad hoc (Burton and Obel 1998, pp. 158–159, Propositions 5.10 and 5.15).	Low differentiation (skill variance) imputes a lower value to structure. Groups (especially small ones) of experts exhibit low degrees of differentiation.
"The more dynamic the environment, the more organic the structure" (Mintzberg 1983, p. 137, Hypothesis 9).	Nonroutine technology: does not favor machine or professional bureaucracy, and routing technology does not favor an ad hoc configuration (Burton and Obel 1998, p. 230, Propositions 7.19 and 7.20).	High urgency and low interdependence together lead to a lower value to structure. These conditions follow when technology is rapidly changing because fast reaction is important in beating competitors, but dependencies between the different tasks are still not known, due to their novelty.
"The more complex the environment, the more decentralized the structure" (Mintzberg 1983, p. 138, Hypothesis 10).	Complex environment: Complex environments, defined as situations where a large number of variables affect outcomes, confound central planning by making a globally optimized solution process less tractable (Burton and Obel 1998, pp. 180–184, Propositions 6.4, 6.6, and 6.8).	A large number of skill sets (high diversity) imputes a lower value to structure. An operating environment with many distinct variables is one where a large number of distinct skill sets are necessary to deal with those variables.

similar properties. Finally, there are different models that might be built using the IVA paradigm that would address many interesting questions.

5.1. Field Research

It would be desirable for future practitioners to be able to give advice about organization structure to companies or whole industries based on those findings of IVA that are not merely extensions of presently known (and more easily applied) rules of thumb. For example, an IVA study

can determine the degree of diversification and differentiation most appropriate for a company expanding into a new market with specific properties. Depending on the levels of task interdependence, differentiation, diversity, load, and urgency, a firm can determine how much guidance to provide for coordinating work in a specific type of project.

To achieve this, the IVA model described above will need to be "calibrated" through field research that is guided by the IVA paradigm. For example, a researcher

might look for the values of parameters like differentiation, interdependence, diversity, load, and urgency in real companies. Assuming total homogeneity of these values throughout the organization enabled us to derive general result applicable to all organizations. We need to know how to aggregate, or average, diverse observed values of the same parameter in the same organization. Such data collection and aggregation methods are the key to calibrating the interaction value and might lend further credence to the idealized, homogeneous model.

The results of the homogeneous models also encourage us to represent specific organizations more precisely by relaxing the homogeneity assumption. IVA parameters clearly can vary across projects or departments in a company. Because the model can be solved/optimized numerically, it should also be possible to make the values of the five parameters heterogeneous for specific consulting purposes. For example, firms can give more resources to more important departments to lower their load. They may value the effectiveness of some parts of the organization more highly than others. Interdependence may also differ between different parts of the organization. As long as the number of variables does not become too large, the partitioned or tiered versions should still be tractable and therefore amenable to numeric solution.

5.2. Mathematical Research

We observed some empirical properties in our investigation that other researchers might prove mathematically. For example, we observed that the attention distribution curves plotted against the ranking of the interaction partner at Nash equilibrium were identical for all parties (see Figure 4). This observation begs for a simple mathematical explanation. The corresponding curve at the global optimum was not as simple. Does it obey a pattern that we have not been able to discern? The assumptions we used in this paper are simple enough that it would be feasible, though tedious, to obtain closed-form expressions for the shapes of the curves. We could also investigate the effects of more fundamental changes in the assumptions. For example, the way in which people choose whom to help might not be based on “first in, first out.” The pattern of request generation and fulfillment might not be completely random as we assumed. For example, what would happen to the two optima under reciprocal selection, i.e., when people respond more readily to requests from those with whom they may wish to interact themselves, or with whom they have successfully interacted in the past?

5.3. Organizational Theory Development

More generally, by imposing bounded-attention constraints on the Huberman and Hogg (1995) model, the modeling framework presented here can be used to pose several interesting questions. For example, we might seek to: Find the best mix of generalists and specialists in the organization; gauge the cost of nagging “bad apples” who use up the time of expert sources who might be of more use to other advice seekers; investigate the ramifications of criteria other than “first come, first served” (e.g., random, tit-for-tat, expectation of future reciprocity) for selecting which advice seeker to help first, when a source has a queue of requests in his or her in-box; impute underlying preferences or competence distributions from the observation of interaction frequencies within a social network of researchers; predict and attempt to control the extent of clique formation in different situations; place upper and lower bounds on the value of trust between parties of an organization; or investigate the effects of skill-level and/or cultural differences among employees of a company proposing to perform similar work in different parts of the world.

It would also be interesting to investigate how systems similar to IVA may be used to model economic situations. What assumptions about utility curves for business interactions would give a similar divergence between the Nash equilibrium and the global optimum for attention allocation? This divergence came about because we strayed from the requirements for a competitive equilibrium as defined by Debreu (1959). The nature of organized work is such that a single interaction partner alone does not add value. This is contrasted to the customary economic-exchange model where goods have intrinsic value and information is considered costless so that free exchange unfettered by a command structure is the only road to the highest utilities for all.

Another economically notable property of the IVA model is that over-utilization of one resource reduces the utility of that resource for all users, including the user who gets a large portion of the resource. Can we perhaps come up with a simpler model that embodies this property, and thus gives a similar divergence between a Nash equilibrium and global optimum? Such a model would be of use, for example, in investigating how and when to use pricing mechanisms vs. regulation for controlling pollution.

Another possible avenue of theoretical research would be to carry out further game-theoretic analyses to determine how a player’s power varies with his pattern of favorites. Power would be defined as value a player can add to any coalition according to Shapley (1953).

Answers to the theoretical speculations that we put forward above would be of interest not only to students of organization theory, but also to mathematicians, economists, geographers, and political scientists.

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