Strategic and Competitive Implications of Business Process Redesign:
Analyzing the Impact of Information Systems and Organizational Design

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Abstract
We analyze the competitive and economic implications of information system design, allocation of decision rights, and task bundling during business process reengineering. The popular reengineering literature advocates employee empowerment — decentralizing decision authority and consolidating tasks — as complementary process redesign strategies. Our analysis reveals, however, that decentralization and consolidation decisions can occur separately, or together; the optimal combination depends on the relative effectiveness of the technology aimed at skill enhancement and the sensitivity of customers to delivery time and quality. We identify those process parameters that can cause decentralization and consolidation to have opposite effects on process performance; we also point at other parameters such as customer to customer variability which can cause them to complement one another. Finally, we explain why in a time-based competitive marketplace, firms are more likely to centralize their decision making while concentrating their information technology investments on enhancing productivity and intra-organizational communications.

1. Introduction

Our research is motivated by a series of process reengineering projects we have done with a Fortune 50 company. The typical approach to reengineering advocates empowerment through decentralizing decision rights and increasing job scope (Hammer and Champy, 1993). However, we find that in this company, that approach did not always work well. Besides, the nature of the information systems that accompany these organizational changes depend on whether tasks are bundled, decision rights are shifted, or both. For instance, service representatives we have observed have been given an increased scope of calls to answer, and an increased number of tasks to perform on site. However, they are not given the rights to make any decisions on replacing certain defective parts, or formulating service or payment strategies tailored to a customer; they either follow a set of rules dictated by a central engineering team, or communicate with experts via their laptops. Though this reduces service duration by allowing one point of contact, the final outcome is not as favorable as one that would result from a thorough analysis of the specific problems presented by the customer. Similarly, in insurance sales, a company may expand the decision scope of their sales agents by allowing them to structure a variety of insurance packages. However, they still retain centralized authority for processing all claims on these packages.

When managers reengineer processes, they are faced with the problem of how much to empower their employees - sometimes, they may believe that total empowerment is not ideal, but they have no guidelines regarding the optimal bundling of tasks and allocation of decision rights. Besides, they face significant difficulties in determining the nature of the new information systems that must be provided to these empowered employees; all these factors affect timeliness, service quality, profitability and service volume in different ways. Our research is aimed at providing such guidelines using a generalized framework, rigorous analysis of the different process design option, and assessing the nature of customer preferences.

Earlier work done in related areas includes, among others, Buzacott (1996), who studies the operational aspects of process design, Clemons, Thatcher and Row (1995), who discuss how the failure of reengineering is related to firm’s lack of understanding of future strategic needs, Clemons and Weber (1994), who examine the role of I.T. in meeting specific customer needs, and Sampler and Short (1992), who discuss how the approach to reengineering depends on the longevity of a firm’s information and expertise.
Sections 2 and 3 describe and analyze our models for sequential specialized task processing and consolidated task processing, respectively. Both sections capture decision rights in a market with variable customer requirements. Section 4 discusses the key strategic and competitive implications of these models. Section 5 concludes and outlines our ongoing research.

2. Decision making with task separation

We analyze the service delivery process of a firm (hence forth, all references to the firm indicate the provider of this service). The process consists two task processing steps (1 and 2). We assume that the ordering of these tasks is pre-determined. Each task has a processing time which is exponentially distributed. Service requests issued by the customers arrive at a Poisson rate $\lambda$. In the absence of any additional information processing entailed by decision making, reading reports etc., the processing rate of a worker handling a single task is $\mu$.

There are two primary forms of information exchange that could take place in processes of this kind: communication between two employees, and communication between the employee and the customer. These elements are fundamental in driving the appropriate job design. To better understand the complexity of these issues, consider a typical insurance policy sales cycle. One employee (typically a field agent) meets with the customer to determine their insurance coverage needs, and estimate the associated risk. This information is then transferred to a second employee who deals with the financial terms and pricing of the insurance package to be offered to the customer. This job is processed sequentially by two different specialists: (1) a field agent who is an expert in relationship management and risk evaluation, and (2) a pricing expert who is skilled in actuarial computations and the design of payment schedules. However, the final decision of what product to offer the customer depends on the two highly interdependent data sets from the customer. The customer may wish extensive coverage with a particular payment schedule which meets their cash flow capabilities. If the insurance company cannot provide a product which meets these coverage needs and payment capabilities, the field agent has to re-negotiate the coverage profile, the payment schedule, or both, and then issues a new proposal to be evaluated by the pricing expert.

An alternate approach is to bundle these two tasks and empower the field agent to handle both coverage and pricing issues. This provides a single point of contact, and allows a single worker to understand and process both data sets before making a decision. However, the agent requires additional training and technology support in order to provide the necessary expertise for both tasks. Besides, the net cycle time of each task is likely to increase due to reduced specialization.

We model these interdependent information sets as two customer specifications information variables $\gamma_1$ and $\gamma_2$. In the case discussed above, $\gamma_1$ corresponds to the desired coverage profile, and $\gamma_2$ corresponds to the desired payment schedule. We assume that both of these specifications variables are uniformly distributed from $-\nu$ to $+\nu$. $\nu$ is a parameter which represents the degree of variability in customer specifications. A low value of $\nu$ would imply that the customer specifications variables $\gamma_1$ and $\gamma_2$ have a low variance; a higher value would imply that there is a wider range of values these variables can take, and therefore, a higher variability across customer specifications. We limit the values of $\nu$ to be between 0 and 1. $\nu = 0$ corresponds to a completely standardized service, while $\nu = 1$ corresponds to highly variable customer requirements. Interpreting the information contained in a particular specification, i.e. determining the value of each $\gamma_i$, requires specialized knowledge (in the example above, the field agent had the specialized skills to determine coverage requirements and risk, and the pricing expert had the expertise to determine the suitability of a payment schedule); the class of knowledge required to perform task $i$ is the same as the class of knowledge required to recognize the value of $\gamma_i$.

The specifications variables described above model customer requirements for a particular job. The values of these variables are independently specified by the customer. However, as described in the example above, it may not be possible to meet both these specifications simultaneously. In our example, if the insurance policy is based solely on the first criterion, and a complete coverage policy is issued, then the deviation from the second specification (desired payment schedule) could be extreme. The same holds for decisions based solely on the second criterion; if the required payment schedule is given, the coverage may be inadequate for the customer’s requirements. Therefore, a policy that minimizes the net deviation from the customer’s requirements is typically chosen. We model the decision made by the service provider as one of choosing a service characteristic value $\delta$ (this is also referred to a service quality). The choice of this variable may be done centrally by a manager, or by one of the workers performing the task. Customer preferences are characterized by a cost of delay and a cost of deviation from their specifications. More precisely, if
Evidently, the firm can charge a higher price if they reduce the costs imposed on the customer. Therefore, there are two (potentially conflicting) objectives — reduction of total time $T$; and reduction of deviation from customer specifications (also referred to as service quality; a deviation cost of 0 corresponds to the highest quality service). Intuitively, a standard service can be provided faster, while high quality service will take longer to provide. We investigate these tradeoffs and their associated organizational costs in a process modeling framework outlined in the next few pages. First, we state a result which characterizes the firm’s optimal choice of $\delta$.

Lemma 1: The value of $\delta$ that maximizes the firm’s profits is

$$\delta = \frac{\gamma_1 + \gamma_2}{2}$$

This is the choice of $\delta$ which minimizes customer costs, and therefore maximizes the price the firm can charge, and would be the quality choice of the firm under ideal conditions. However, this assumes three conditions: that the specifications information ($\gamma_1, \gamma_2$) can be accurately determined by the decision maker, that the determination of these values and the delivery of the corresponding service is costless. Certain delay related costs, fixed organizational costs and information barriers may preclude the occurrence of these conditions. In the following sections, we also try to estimate the impact of violating these conditions.

2.1. Centralized decision making with specialized task processing

Our base case is one of centralized decision making and specialized task processing, and is illustrated in Figure 1(a). The service characteristic decision is made centrally. The tasks are then performed sequentially by separate workers. Realistically, a service characteristics decision cannot be made centrally for every instance of the service, as this entails additional information transmission delays and decision making delays. Instead, we assume that a standard decision is mandated; this will be the one that minimizes expected deviation from customer specifications over the state space of customer specifications information. The mandated decision that minimizes this deviation is $\delta = 0$ (this is easily verifiable). With this adjustment, a firm which provides optimal service quality can always charge a maximum of $p_0$.

If the customers specifications are $\gamma_1$ and $\gamma_2$, then the choice of $\delta$ that minimizes the net deviation $(\gamma_1 - \delta)^2 + (\gamma_2 - \delta)^2$ is $\delta = (\gamma_1 + \gamma_2)/2$. If this value of $\delta$ is chosen by the firm, then the adjustment ensures that net quality cost imposed on the customer is zero.
The profits to the firm per unit time are therefore

\[ \pi_{SC}(\lambda, v) = \lambda[p_0 - \frac{2c_D}{\mu - \lambda} + \frac{c_Q v^2}{3}] = p_0\lambda - \frac{2c_D\lambda}{\mu - \lambda} - \frac{c_Q v^2\lambda}{3} \]

The following result can be immediately inferred:

**Lemma 2:** Under centralized decision making and specialized task processing, the profits of the firm are decreasing in the level of customer variability.

This can be proved easily by verifying that \( \frac{\partial \pi_{SC}}{\partial v} \) is negative. Having analyzed our base case, we now investigate the effects of decentralization of decision making, and consolidation of tasks.

### 2.2. Decentralized decisions with specialized task processing

The first common form of process reengineering we consider is the decentralization of decision authority. As mentioned earlier, the knowledge required to perform task \( i \) is the same as the knowledge required to observe and interpret \( \gamma_i \). Therefore, when successive specialists perform their tasks, the specialist who performs task 1 has the skills required to determine the value of \( \gamma_1 \), and the specialist who performs task 2 has the skills required to determine the value of \( \gamma_2 \). However, specialist \( i \) does not possess the knowledge required to determine the value of \( \gamma_j \), \( j \neq i \).

Consolidating and interpreting specifications or requirements is not costless in terms of delays; besides, customizing a service requires an additional processing effort. With these points in mind, we assume that if worker \( i \) determines \( \gamma_i \) and chooses a value of \( \delta \) based on that observation, then the processing rate of worker \( i \) is reduced by a factor \( \alpha_i \), which depends on the degree of customization \( v \). Since the task processing is sequential, the determination of \( \delta \) will have to be made by the first worker.

Suppose the decision making is decentralized to the first worker. This worker determines the value of \( \gamma_i \), but has no information about the value of \( \gamma_2 \). Assume that incentives are aligned, and the worker wishes to make a decision that is optimal for the firm (this can be ensured by tying the worker’s performance to service quality).

Suppose the decision made is \( \delta \). The total cost imposed on the customer during the processing of the first task is

\[ c_1 = \frac{c_D}{\alpha_\mu - \lambda} + c_Q(\gamma_1 - \delta)^2 \]

Also, the expected cost imposed on the customer in the second stage is

\[ c_2 = \frac{c_D}{\mu - \lambda} + \frac{c_Q}{2v} \int (\delta - x)^2 \, dx \]

The worker chooses the value of \( \delta \) that minimizes total costs \( c = c_1 + c_2 \). However, this value is \( \delta = 0 \). This can be verified by solving \( \frac{\partial c}{\partial \delta} = 0 \), and leads to our next result:

**Proposition 1:** In the absence of any additional information sources, in a specialized sequential process design, decentralizing decision making is strictly inferior to centralized decision making.

The result follows from the fact that the service time of the first specialist increases by a factor \( \alpha_\mu \), due to the added effort. However, the average quality remains the same. The natural question which one poses at this point is whether a specialized worker can receive and process information that is not directly related to her specialty. This is possible in the presence of a information sharing system. We build on approaches used by Marschak and Radner (1972) and Carter (1995) in defining and analyzing the presence of this kind of information system.

### 2.3. Decentralized decision making with an information sharing system

From the analysis in the previous section, it is evident that some kind of additional information system is required to decentralize decision making in a specialized task processing environment. One such system is an information system that enables information sharing between the two workers. The process and information flows using such a system are illustrated in Figure 1(b). Such a system could enable the second worker to transmit information related to \( \gamma_i \) to the first worker. However, it is likely that there will be some error introduced in the information transmitted, due to the fact that worker 1 has no specialized knowledge related to \( \gamma_2 \), and that the observation of the information and the use of the information are by different individuals. We therefore define an information sharing system as one which takes as an input a specification information variable \( \gamma \) and returns a report \( \gamma + \varepsilon(x) \) where \( \varepsilon(x) \) is normally
distributed with mean 0 and variance \( \sigma^2 \), i.e. \( \epsilon(x) = N(0, \sigma^2) \). The value of \( \sigma \) is a reflection of the quality of the information sharing system (a higher variance implies a higher transmission error and thus an inferior information system). It is also increasing in \( \nu \) - for simplicity, we assume that it is linear in \( \nu \). For modeling tractability, we also assume that the process of determining \( \gamma_1 \) is costless\(^3\) to worker 2. However, the delay generated by reading and interpreting the output of the information system causes a further reduction of \( \alpha \) in the processing rate\(^3\) of worker 1. Worker 1 now knows the values of the two specifications information variables as \( \gamma_1 \) and \( \gamma_2 + \epsilon \). The choice of \( \delta \) is therefore \[ \delta = \frac{\gamma_1 + \gamma_2 + \epsilon}{2} \], and the expected cost imposed on the customer is:

\[
c = c_D\left(\frac{1}{\mu - \lambda} + \frac{1}{\alpha^2 \mu - \lambda}\right) + c_Q \int_{-\infty}^{\infty} \left\{ \frac{\gamma_1 + \gamma_2 + \epsilon(x)}{2} - \gamma_1 \right\}^2 dx
+ \left( \gamma_1 + \gamma_2 + \epsilon(x) - \gamma_2 \right)^2 dx
\]

\[
= c_D\left[\frac{1}{\mu - \lambda} + \frac{1}{\alpha^2 \mu - \lambda}\right] + c_Q \sigma^2 \epsilon^2
\]

The expected profits of the firm are therefore:

\[
\pi_{SD}(\lambda, \nu) = \lambda [p_0 - \frac{c_D}{\mu - \lambda} - \frac{c_D}{\alpha^2 \mu - \lambda}] - \frac{c_Q \sigma^2 \epsilon^2}{4 \nu}
\]

Examining these expressions leads to our next result:

**Proposition 2:** Decentralized decision making becomes more desirable as:

(a) the degree of customization increases, and
(b) the quality of information sharing systems increases

However, the optimal demand for the firm reduces significantly, and the non-decision making worker could be under-utilized.

### 3. Decision making and task bundling

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\(^3\) This could be a reflection of the nature of the information system. One can assume that worker 2 is just required to enter a few details about the specifications information, and an expert system generates a report understandable to worker 1.

\(^3\) One may wonder why the reduction is the same variable \( \alpha \). Arguably, when much of the information processing has been done by an information system and by worker 2, the value of this parameter should be lower. However, the specifications are not in the area of specialty of worker 1, and this can increase the loss in productivity. Assume these effects cancel out.

The potential gains from consolidation of decision related information with a single worker lead to the possibility of consolidating tasks and increasing the scope of knowledge of the workers so that a single worker has the skills required to interpret both specification information signals and perform both tasks. There are two common process designs that allow for this scenario; parallel generalists with a shared queue and triaged generalists with separate queues. In both cases, the workers are provided with the skill set required for both tasks; this enables them to make more informed decisions, and may also reduce the queuing delays of the process by consolidating queues, or from reduced variability in processing time. We assume that at ideal skill levels, the processing of the two consolidated tasks is exponentially distributed with parameter \( \mu/2 \). This allows us to use a number of closed form results for \( M/M/s \) queues.

However, there is also a loss of specialization when tasks are consolidated. This causes a net reduction in the processing rate of a worker working on consolidated tasks. The magnitude of this loss of productivity depends on the knowledge intensity of the tasks, and the quality of information systems support. We model this loss in productivity by the factor \( \beta (0 < \beta < 1) \). When tasks are consolidated, the processing rates of a worker working on consolidated tasks is exponentially distributed with parameter \( \beta \mu/2 \).

The value of \( \beta \) is not fixed - it can be influenced by information systems that enhance worker skills, such as expert systems, case based reasoning tools etc. We return to this point in Section 4 and detail our modeling assumptions about the relationship between \( \beta \) and the information systems design.

### 3.1. Centralized decision making and task consolidation

This section examines centralized decision making and consolidated tasks in a consolidated task setting. All the general assumptions of section 2 are still valid, as are those described in the preceding paragraphs. Decentralized information is not used; the firm mandates the service characteristic that minimizes its quality costs.

**3.1.1 Parallel generalists; shared queue.** In the case of a shared queue, the centralized decision policy is still \( \delta = 0 \), as this minimizes expected customer quality costs. The queuing system is an \( M/M/2 \) with arrival rate \( \lambda \) and service rate \( \beta \mu/2 \). See Figure 2 (a). The expected costs imposed on the customer are given by
3.1.2 Parallel generalists; triaged system. Triage is normally aimed at reducing processing time variability. However, there are other competitive and strategic implications of separating services into parallel separate queues. One possible implication could be the reduction in specifications information variability. If the jobs are partitioned into two parallel streams, one of which consists of service requests where $\gamma_1 > 0$, and another where $\gamma_1 < 0$, then a centralized decision making scheme could be more effective, as the specifications information variability goes down, thereby reducing the quality costs imposed on the customer. We state without proof that the optimal division policy is to bisect the jobs along one dimension of specifications i.e., separate them into jobs with $\gamma_1 \geq 0$ and $\gamma_1 \leq 0$. This produces two equal streams of jobs with arrival rates $\lambda/2$.

We consider the positive half ($\gamma_1 \geq 0$); by symmetry, the other half have similar results. Let the optimal decision policy mandated by the centralized decision maker be $z \geq 0$ (it is evident that $\delta$ will be positive for the positive stream). The expected quality costs from this policy are:

$$c_1 = c_Q \left\{ \frac{1}{2} \int_{-v}^{v} \int_{-v}^{v} [x - z]^2 + (y - z)^2 - \frac{(x - y)^2}{2} \, dy \, dx \right\}$$

where

$$W_Q = \frac{2\lambda^2 p_0}{\mu (\mu - \lambda)}; \quad p_0 = 1 + \frac{2}{\beta \mu} + \frac{8\lambda}{\beta^2 \mu^2 (4 - \lambda \beta \mu)}$$

The expected profits per unit time are therefore:

$$\pi_{PC}(\lambda, v) = p_0 - c_D[W_Q + \frac{1}{\beta \mu}] - \frac{c_Q v^2}{3}$$

$$= p_0 \lambda - c_D[W_Q + \frac{1}{\beta \mu}] - \frac{\lambda c_Q v^2}{3}$$

The quality cost minimizing solution is at $\frac{\partial c_1}{\partial z} = 0$ or $z = \frac{v}{4}$, which yields $c_1 = c_Q \frac{v^2}{12}$. This reflects a net reduction in quality related costs of 75%. A similar approach for the negative stream yields $z = -\frac{v}{4}$ and
identical quality related costs \( c_i = c_Q \frac{V_i^2}{12} \). The delay costs in this case are \( \frac{2c_D}{\beta \mu - \lambda} \). Therefore, the expected profits per unit time are given by

\[
\pi_{TC}(\lambda, \nu) = \lambda[p_0 - \frac{2c_D}{\beta \mu - \lambda} - \frac{c_QV^2}{12}] 
= p_0\lambda - \frac{2c_D\lambda}{\beta \mu - \lambda} - \frac{c_QV^2\lambda}{12}
\]

3.2. Decentralized decision making and task consolidation

Since the workers have the skill set to perform both tasks, it is natural to assume that they have the ability to determine the values of both \( \gamma_i \) and \( \gamma_2 \). This leads to the final process design we consider, where tasks are consolidated and decision making is decentralized. We assume that the supporting information systems enable the workers to not only perform both tasks, but also provides decision support in terms of indicating the value of \( \gamma_i \) and \( \gamma_2 \). Since there is some attrition in the skill sets of the workers (as compared to a specialist), they cannot observe the true values of \( \gamma_i \) and \( \gamma_2 \). Instead, as in section 2.3, they observe values \( \gamma_i + \varepsilon_i, \gamma_2 + \varepsilon_2 \), where \( \varepsilon_i \sim N(0, \sigma_i^2) \).

As before, \( \sigma_i^2 \) depends on the range of customization \([\nu, \nu\nu]\); however, it also depends on the quality of the supporting information system that provides this information, and the information systems that enhance worker skills. Evidently, if the technological infrastructure is one that allows for almost complete compensation for losses from reduced specialization, then \( \sigma_i^2 \) will be much lower. Again, as in the case of \( \beta \), we return to this issue in Section 4 and detail our modeling assumptions in this regard.

As in the sequential case, determining and using these values reduces the processing rate of a task by a factor \( \alpha_i \). For comparability, we assume that this factor is the same as that of the sequential specialist case.

3.2.2 Parallel generalists; triaged system. We have two parallel \( M/M/1 \) queues with processing rates \( \alpha, \beta \mu \) and arrival rates \( \lambda, \nu/2 \). The expected costs imposed on the customer are given by:

\[
\pi_{PD}(\lambda, \nu) = \lambda[p_0 - c_D[\frac{1}{\alpha \beta \mu} - \frac{c_Q\sigma_i^2}{2\nu}] 
+ \frac{c_Q^2}{2\nu} \int_{-\infty}^{\infty} \left[ \frac{\gamma_1 + \gamma_2 + \varepsilon_i(x) + \varepsilon_2(x)}{2} - \gamma_1 \right]^2 
+ \left[ \frac{\gamma_1 + \gamma_2 + \varepsilon_i(x) + \varepsilon_2(x)}{2} - \gamma_2 \right]^2 
\right]
\]

\[
= c_D\left[ \frac{2}{\alpha \beta \mu - \lambda} + \frac{c_Q(\sigma_{\varepsilon_1}^2 + \sigma_{\varepsilon_2}^2)}{4\nu} \right]
= c_D\left[ \frac{2}{\alpha \beta \mu - \lambda} + \frac{3c_Q\sigma_{\varepsilon}^2}{8\nu} \right]
\]

Therefore,

\[
\pi_{PD}(\lambda, \nu) = \lambda[p_0 - c_D[\frac{2}{\alpha \beta \mu - \lambda} - \frac{3c_Q\sigma_{\varepsilon}^2}{8\nu}] 
\]

\[
= p_0\lambda - \frac{\lambda c_D}{\alpha \beta \mu - \lambda} - \frac{3c_Q\sigma_{\varepsilon}^2}{8\nu}
\]

4. Strategic and Competitive Implications

The availability of multiple process designs has important strategic and competitive implications for a corporation. The design of the business process and its accompanying technology can be chosen based on the strategy that the firm wishes to follow. Alternately, the strategy chosen by a firm may be a consequence of its technological infrastructure, and the nature of the service provided. In a competitive market, one such strategy may be profit maximization through rapid service turnaround, if customers have high delay costs. Another strategy, possibly by a market entrant, could be gaining market share (possibly with a short term lowering of profits) with
the objective of increasing expected future profits. A third could be profit maximization through market segmentation - if customer preferences are highly variable, tailoring services to meet the specific needs of particular market segments may be a successful strategy.

Once a strategy is chosen, the process design that best suits this strategy must be implemented. We examine the strategies outlined above in the context of our service model. Our analysis is based on the assumption that the direction of causality is from markets and services to firms; that is, there is a set of market characteristics, task parameters and technology choices that a firm does not cause or influence. Instead, it has to react to these parameters by choosing a service strategy and designing business processes that best suit this strategy. One firm specific characteristic that we examine is the technological maturity of the organization and workers — how well the firm and its employees can leverage existing technology to their advantage. For instance, a firm with a strong technology culture, or a well established learning infrastructure can expect better skill enhancement returns from information systems, and lower productivity losses from task consolidation.

4.1. Information systems for specifications interpretation and skill enhancement

As mentioned earlier, technology can influence the productivity losses faced by workers when tasks are consoliated, and can facilitate superior interpretation of specifications when specialized workers need to understand diverse customer requests. Information systems such as expert systems and case based reasoning systems can increase the value of $\beta$, or reduce the variance of the error term ($\sigma^2\varepsilon$) of $\gamma$. We assume that the firm chooses a technology level $\theta$, which costs them $c_\theta \theta$, and which influences these parameters as described below.

We have observed in practice that the productivity gains from skill enhancing technologies are increasing at a decreasing rate (i.e., increasing and concave). One reason for this is that significant gains can be achieved by providing workers with simple case based reasoning systems; however, the additional information support required to go beyond these gains is extremely high. Another reason is attributable to the nature of knowledge — it is easy to capture heuristic rules that apply to broad ranges of cases, but virtually impossible to build a system that goes beyond this form of reasoning and can actually facilitate understanding of the concepts underlying these rules, or that can successfully handle exceptions. With this functional form in mind, we model the relationship between $\beta$ and $\theta$ as

$$1 - \beta = (1 - \beta_0)e^{-\beta_1 \theta}$$

where $\beta_0$ reflects the base knowledge intensity of the tasks ($\beta_0 \in (0,1)$, lower $\beta_0$ means higher knowledge intensity), and $\beta_1$ is the sensitivity of the tasks to increased technology support ($\beta_1 \in [0,\infty)$, higher $\beta_1$ means higher returns from technology). $\beta_1$ could be a characteristic of the tasks, or an attribute of the firm.

Similar reasoning goes into our functional form for $\sigma^2\varepsilon$. However, the variance of $\varepsilon$ is also dependent on the range of customer specifications $[\gamma_1, \gamma_2]$.

For simplicity, we assume it is linear in $\gamma$. The exact functional form we assume for the variance of $\varepsilon$ is:

$$\sigma^2\varepsilon = \sigma^2_{\varepsilon 1} = \sigma^2_{\varepsilon 2} = \frac{\sigma_{\varepsilon 0}^2}{2} e^{-\gamma_1 \theta \gamma - (\gamma - \gamma_1)} = \nu \sigma_{\varepsilon 0}^2 e^{-\gamma_1 \theta \gamma} = \sigma_{\varepsilon 1}^2$$

for a sequential system or a shared queue, and

$$\sigma^2_{\varepsilon 1} = \frac{\sigma_{\varepsilon 0}^2}{2} e^{-\gamma_1 \theta \gamma - (\gamma - \gamma_1)} = \frac{\nu}{2} \sigma_{\varepsilon 0}^2 e^{-\gamma_1 \theta \gamma} = \sigma_{\varepsilon 2}^2 / 2$$

$$\sigma^2_{\varepsilon 2} = \frac{\sigma_{\varepsilon 0}^2}{2} e^{-\gamma_1 \theta \gamma - (\gamma - \gamma_1)} = \nu \sigma_{\varepsilon 0}^2 e^{-\gamma_1 \theta \gamma} = \sigma_{\varepsilon 1}^2$$

for a triaged system.

The variance of error is linear in the degree of customization, and decreasing in the level of technology support. With no customization, there is no error (evidently, since $\gamma_1 = \gamma_2 = 0$), and with very high technology support, there is negligible error. Since the range of values is halved for $\gamma_1$ in a triaged system, so is the variance of the error.
4.2. Strategies that maximize single period profits

Consider the case where a service comprises tasks that are knowledge intensive ($\beta$ is low), and that returns from information systems that compensate for skill attrition are not high ($\beta_i$ is low, $\epsilon_1$ is low). We performed numerical optimization of the profit functions for a wide range of parameter values. Sample results are shown in Figure 3. Our findings were consistent over a wide range of values, and are summarized in Proposition 3.

**Proposition 3:** When a service is knowledge intensive, and a firm’s returns from skill enhancing information systems are low, then a system with task separation and centralized decision making is optimal. Decentralization is rarely optimal because the benefits from higher service quality are dominated by the cost of information sharing technology and the revenue loss from reduced service throughput.

This result was invariant over a fairly wide range of quality and delay costs. It is reflective of the fact that decentralization of decisions that require knowledge in more than one area (which covers most product customization decisions) is very difficult to do in a functional organization. We also observe that there are services and firms for which the ‘universal solution’ of decentralized decision making by enabled multifunctional workers is not the optimal choice.

This result also illustrates the contradictory nature of some of the textbook suggestions for BPR. A person with a high level of knowledge related to a particular task is in a better position to interpret customer specifications of that task, and therefore do a better job if given decision authority. Besides, customers of services that comprise tasks that are knowledge intensive are more likely to place a high premium on their specifications being met. However, in such services, though consolidating tasks improves the potential for better decision making, it also reduces the cycle time of the process significantly. Therefore, we have cases in which task consolidation and decentralization produce opposite effects on process performance, rather than complementing one another.

There are a large number of services for which though skill attrition from consolidation exists, it can be sufficiently compensated for by technology support ($\beta_i$ and $\epsilon_1$ are not low). This is characteristic of services which are not so knowledge intensive ($\beta_0$ and $\epsilon_0$ are not low), and for which it is not difficult to acquire task knowledge through systems support. We investigated systems with these parameters. Our results, which are summarized in Proposition 4, indicate that task consolidation is the ideal solution - however, whether queues should be consolidated, and decisions decentralized depends on other process parameters.

**Proposition 4:** When the returns from skill enhancing information systems are moderate or high, then task consolidation is optimal.

(a) When customers are time sensitive, then centralized decision making is optimal.

- If specification variability is high, then triaged systems are ideal.
- If specification variability is low, then shared queues are optimal.

(b) When customers are quality sensitive, then decentralized decision making is optimal.

- If the returns from information systems that provide specifications interpretation support are high, then shared queues are optimal.
- If the returns from these systems are relatively lower, then triaged systems are optimal.

Figures 4 and 5 show some of the results from our analyses in this region. With only low to moderate skill attrition from consolidation, we expect the optimal process design to be non-sequential. However, interestingly, task consolidation and decentralization do not always accompany one another. As Proposition 4(a) shows, the sensitivity of customers to delays results in...
Centralized decision making to reduce cycle time. We also see that in the presence of high customer variability, a triaged work system which reduces quality deviation costs can be preferable to a shared queue system which minimizes queuing delays. This indicates that triage provides a good balance between reducing delays and reducing quality costs, if the customers value time more. On the other hand, when customers are quality sensitive, decentralization accompanies task consolidation. Since their sensitivity to delay costs is not relatively high, the gains from reduced delays can be sacrificed for better quality through triage when \( \varepsilon_1 \) is low (i.e. when a relatively high technology level is required to reduce the quality of decision making in a consolidated system. The tradeoff is increased delays; however, the quality sensitivity of the customers makes the triaged system ideal in the face of high specifications variability.

4.3. Strategies that maximize market share

Section 4.2 examines profit maximizing decisions. However, there are situations in which this may not be the only criterion of importance. An equally important competitive factor is market share. In our model, the value of \( \lambda \) that maximizes profits can be taken as a measure of the share of the market that a firm captures (the higher the throughput, the larger the number of customers served). This approach leads to our next proposition

Proposition 5: If the objective of a firm is to capture market share then task consolidation is optimal.

(a) If the market is uniform in terms of time preferences, then a shared queue system is likely to make a firm more competitive. Centralized decision making is superior in this scenario. However, short term profits are lower if the market is quality sensitive

(b) If the market is non-uniform in terms of time preferences, then it is likely that a triaged system will dominate.

We find that task consolidation and centralized decision making is the ideal strategy for capturing market share in a variety of situations. In a time sensitive market, the profit maximizing strategy also maximizes market share, except when variability is high. However, the triaged process design significantly improves market share at higher values of variability. Hence, the short term profit maximizing strategy is also optimal as a long term competitive strategy. However, the decentralized process designs that were optimal for profit maximization did not yield market share maxima; on the other hand, they were dominated by centralized solutions. The competitive implications of this are clear; in a market where customers are quality conscious, firms may sacrifice short term profits for long term market share, or vice versa.

We are currently investigating the implications of heterogeneous time preferences among customers.

5. Conclusions

We have investigated the competitive and economic implications of information technology, decentralizing decision rights and consolidating tasks during process reengineering. Figure 8 summarizes our findings. The

![Figure 8](image)
The analysis of several process design parameters shows that in a time-based competitive marketplace, centralized decision making and bundled tasks are clearly superior to other process designs; hence, information technology investments should be directed at increasing skill levels (so that loss of expertise from task consolidation is minimized) and at improving communications between the line workers and management (so that the centralized decisions are better informed decisions). As indicated in the lower right quadrant of Figure 8, the work system (shared vs. separate queues) depends on the variability in customer demands. On the other hand, a firm facing competition on quality may lose out on market share if it focuses on profit maximization in the short run. It may be necessary to decentralize decision rights if the variability of customer specifications is high; however, care must be taken that this does not adversely affect the firm’s capacity. Information technology that enhances information access and sharing is a good choice here. Systems such as decision support systems that minimize information losses and provide timely access to diverse information are likely to be adopted by firms in such markets.

Our ongoing research examines the different process designs that are optimal for a firm facing heterogeneous time preferences. We also study the optimal incentive contracts that a firm needs to implement as a function of the relative consumer preferences for timeliness and quality. Our preliminary results indicate that, regardless of the level of information technology, decentralization must be accompanied by performance-based incentives; however, the choice of performance measures must depend on the nature of the customers and the competitive offerings available in the marketplace.

6. References


