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INFORMATION SYSTEMS, INCENTIVES AND WORKFLOW LOGIC: STRATEGIC IMPLICATIONS FOR REENGINEERING BUSINESS PROCESSES

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Abstract

We use a series of case studies to motivate the analysis of the organizational impact and performance associated with information systems and workflow design topologies. Our study places a special emphasis on processes involving information intensive tasks that require information sharing and extended information access. The role of various information technologies is examined in the light of their effects on process workflows, worker incentives and worker performance. Our analytical research framework incorporates the effects of queuing lead times, incentives, data sharing and the consolidation of tasks. We show that the following task attributes — *information intensity*, *skill requirements*, *specifications variability*, and *technology returns* — have a critical role in the success of process redesign. We prove that technology that streamlines information flows not only improves job control, but can also reduce the cost of incentive compensation. Our results also explain why, under certain circumstances, information technology investments and enhanced worker incentives are substitutable. We conclude with several managerial guidelines for process redesign.

1. INTRODUCTION AND RESEARCH MOTIVATION

We develop a framework aimed at analyzing the optimal choice of information systems, workflow topologies and incentives for processes that involve information intensive inputs and tasks. Our research is motivated by our ongoing field studies of on several process redesign projects at a Fortune 50 corporation. To better understand the dilemmas facing managers who redesign business processes, consider, for instance, the case of one such project which involved travel expense reimbursement for over ten thousand national sales representatives. The existing process in this corporation consists of five steps. The employee submits her travel details. An HR specialist determines the appropriate reimbursement rates (which depend on geographical location, car model, time of year, etc.). An administrative assistant then prepares a standard expense report. This is forwarded to a manager for approval. The manager examines this report, and if approved, forwards it to the payroll department. The final step is data entry into the legacy payroll system.

If one follows the general rules proposed by Hammer and Champy (1993), there are a couple of feasible approaches to redesigning this multi-step process. One approach involves employees determining their expense rates and filing their reports electronically. The reimbursement amount would be automatically forwarded to the payroll system, the payroll files updated, and the amount deducted from the employees' budget center. This conformed with two rules of reengineering: "doing work where it most makes sense" and "reducing checks and controls." However, it involves company-wide distribution and maintenance of new software — a very expensive proposition. Remote information access of the specialized information owned by HR could prove fairly slow, and decentralized maintenance of this information would be expensive and unreliable. The process owner also wondered what kind of incentives would ensure that employees reported accurate figures. Besides, direct access to the legacy payroll system posed immense problems.

The other approach is along the lines of the IBM Credit case of Hammer and Champy. It involves the creation of expense account officers who use shared databases and a validation expert system to calculate reimbursement amounts. Exceptions are rerouted to the employee's manager for approval, and a feed to the payroll system allows updating of the relevant records. The process owner was still reluctant to adhere blindly to the rules of task consolidation. It was difficult to estimate whether the cost of the additional technology was justified. Besides, the specialists in the existing process were highly productive and efficient — could one expect a generalist to have the same productivity, even with extensive technology support? Would the expected cycle time reduction from this redesign be negated by increased queuing delays? Would the expanded job responsibilities warrant increased or modified compensation?

It is possible that the existing sequential system, if streamlined and automated, might yield the best performance — however, this was contrary to "conventional" reengineering philosophies. Unfortunately, reengineering case studies and books offered no broadly applicable principles that the process owner could follow, because there was no formal theory which indicated what combination of job parameters, incentives and technological options warranted a particular process design – this is the gap which our research aims to fill.

Our case studies reveal that the primary forms of information technology used in reengineered processes are technologies that enhance information sharing and access, broaden the skill set of employees, and increase their processing rates. A related issue is the control structures over information flows and workflow topologies enabled by the technological infrastructure. We include all these technology *effects* in our model. Another key issue is information ownership and location — we have addressed this in a separate paper.

Our studies also reveal that examining technology issues in isolation is inadequate. The value of an information system is determined not only by its performance or features, but also by how well it complements the processes it supports and enables. Therefore, the other aspects of a business process that affect information systems — the structure of incentives and the topologies of process workflows (workflow logic) — are explicitly modeled in conjunction with the effects of technology.

In the next section, we provide an overview of the scope of our model. In section 3, we describe the model and detail results related to the optimal design of a business process. In section 4, we conclude and list the managerial insights from our model, as well as outlining our ongoing and future research.

2. MODELING INFORMATION INTENSIVE PROCESSES: AN OVERVIEW

The optimal design of any business process is determined by a number of factors. Our model separates these factors into *job-specific parameters* and *process design parameters.* We classify process design parameters into three categories: information technology, control over job information, and the structure of systems for measuring and rewarding performance. In the subsequent discussion, the term *job* refers to a particular instance of a process and the term *task* refers to a particular activity that is necessary for the successful completion of a job; a job is therefore a collection of tasks. For instance, in our earlier example, reimbursing a particular employee for a specific month is a single job; determining the appropriate reimbursement rates for this employee is one of the tasks that constitutes this job.

Any process has an objective. This objective determines what it adds to the information that constitutes its input: for instance, the objective of the reimbursement process we described is to determine how much to reimburse an employee. The input to this process is the travel details and its output is the additional information of how much to add to the employee's paycheck. *The job-specific parameters* of a process are the parameters that characterize the *information that constitutes the input* to the process, and the *information that flows with the job* within the process. We generalize the nature of a job to be determined by the level of supporting functional information required to complete the job (*the information intensity*), the variability in customer requirements *(the specifications variability)*, the specialization requirements of the tasks in the job (*the skill requirements)* and the interdependence between the different tasks in a process *(the information sharing)*. These measures will be explained in detail in section 3.

The *process design parameters* determine *how* the objective of the job is accomplished. Our first class of process design parameters, those related to *the process workflow topology,* determine how the *control over job information flows* is managed (we refer to these as the *workflow logic]* parameters). These determine which worker has control over the job information at any given moment. Some rules relate to job triaging; other rules may relate to task allocation and sequencing. For instance, if worker A determines reimbursement rates, and worker B prepares expense reports, and the first task precedes the second, then these rules determine that worker A gets control over the task information first, and worker B gets control after worker A.

In manufacturing settings, the control of a job lies with the machine that is currently processing the physical product (or has it in its queue). Earlier, control in service settings could be determined by who had the file of papers or documents related to the job; however, current technology allows these documents to be stored in a shared database. The physical flow of a file has been replaced by the logical flow of *control* over the job information, which can be difficult to manage and streamline. For instance, there is often a lag between the instant one worker finishes a task and the instant the next worker is *aware* that she has control over the job information. Therefore, it is necessary to design a process that minimizes these non-value adding delays. The emergence of case managers and cross-functional teams who control a job from start to finish is evidence that the service industry recognizes the inefficiencies of sub-standard control, and the difficulties in managing control in information intensive jobs.

The second class of parameters consists of the *information architecture* parameters. Our classification of information technology is based on its broad effects and characteristics for many reasons. In order to enable business-driven development of new technology, it is necessary to identify what effects or functionality firms value most in information systems. Besides, a sound analysis of the value of certain technology effects and their interplay with the other organizational variables we study gives managers an idea of the long-term strategic benefits and effects of information systems. If new technology becomes available in the future, results that are based on the general effects of IS rather than on hardware specifics are still of value.

The class of information architecture parameters we focus on relates to the *direct effect* technology has on *worker performance*. This includes support directed at increasing workers processing rates via better information access or automated processing (e.g., enterprise-wide document servers, spreadsheets, task "wizards" that automate repetitive typing), expanding their expertise (e.g., decision support systems, expert systems), and enhancing information sharing (e.g., workgroup software, intranet-based document sharing systems).

The control of information flows is closely related to the information architecture. Workflow automation software such as SAP's R/3 is directed at improving process performance by streamlining information flows and improving control over information. Intranets allow universal access to information; processes that use this technology may eliminate the need for the flow of information, replacing it by the flow of access control. We examine the implications of these technology effects as well.

The third class of parameters are the *performance measurement and control* parameters. In our current model, we focus on the incentive structures that determine how worker performance is measured and compensated. (The reader is referred to Eisenhardt [1985] for a discussion of approaches to modeling performance control). We examine the allied issue of decision authority in a related paper (Seidmann and Sundararajan 1997).

Our process model is summarized in Figure 1. Prior work related to process reengineering has consisted mainly of case studies and broad recommendations (Champy 1995; Davenport 1993; Davenport and Short 1990; Hammer 1990; Hammer and Champy 1993) Existing analytical studies have examined some of these parameter classes in isolation; work flows (Buzacott 1996) information and technology (Sampler and Short 1994; Whinston, Lee, and Barua 1995) and performance measures and compensation (Brickley, Smith and Zimmerman 1995). Our model is designed to capture all these process parameters and design variables.

3. TECHNOLOGY, INCENTIVES AND WORKFLOW LOGIC

We model a process in which each job consists of *n* tasks. The time it takes to process a task is a random variable; the mean processing time of task i is $1/\mu_i$, and the processing times of different tasks are independent. The task sequence is pre-determined, i.e., task 1 must be performed before task 2, etc. We make this assumption in order to focus on process design parameters other than the optimal task order. Jobs arrive according to a Poisson process with rate λ. Different tasks may be performed by different workers, or by the same worker.

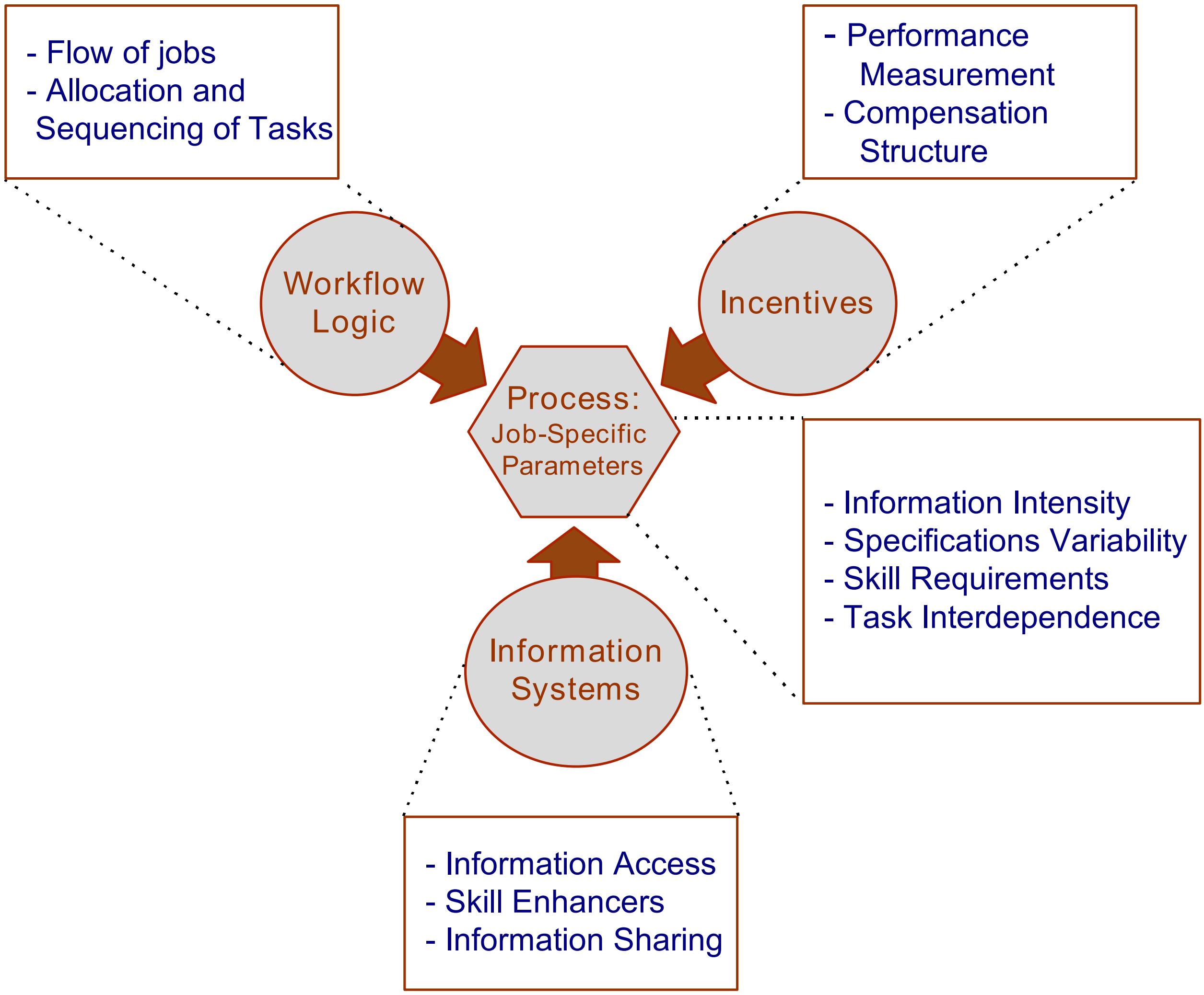

Figure 1. Business Process Attributes

3.1 Job-Specific Parameters

Each process has the *job-specific* parameters:

- A *specifications variability* parameter $\sigma \in [1, \propto)$. This parameter measures the magnitude of customer or case-specific information that is required for the successful completion of each task, and it determines the magnitude of the delay whenever a job is handed off from one employee to another. The delay is a consequence of rereading specifications information. σ=1 corresponds to no specifications variability (all jobs are standard). The higher the specifications variability, the higher the value of σ, and the higher the resulting *handoff* delay.

- An *information intensity* parameter $\alpha_0 \in [1,\infty)$. This measures the level of functional information (from an outside functional department/specialized information system) needed to successfully complete a task[1] and determines the level to which the performance of the tasks is dependent on the accessibility of specialized information. $\alpha_0=1$ corresponds to a situation where no specialized supporting information is required. A high value of α_0 corresponds to jobs that require a large volume of specialized information.

- A *skill requirements* parameter $\beta_0 \in [0,1)$. This measures the degree of functional specialization or expertise required to successfully complete a task. $\beta_0=0$ corresponds to the lowest expertise requirements (no gains from specialization); a value of β_0 close to 1 corresponds to the highest expertise requirements (only a specialist can perform the tasks of the job).

- A *task interdependence* factor $\tau_0 \in (0,1]$ that measures the *information sharing* required by two tasks if they are performed by *different* workers; for instance, the level to which the results of one task must be understood in order to perform the next task. $\tau_0=1$ would imply that the tasks are completely independent. τ_0 close to 0 means that there is a very high level of information sharing between two tasks. This is distinct from the first parameter (specifications variability), which measures how much different jobs differ. If detailed understanding of the results of the first task significantly influence the second task, then task interdependence is high (and the value of t_0 is low). On the other hand, if level of customization is high, and customers have highly variable requirements, the value of s_0 is high.

3.2 Workflow Logic

We model a functionally specialized process and two typical reengineered process designs: a process involving multifunctional generalist, and a process that uses a cross-functional team. To enable a concise analysis, we analyze a set of two tasks. The intuition that is gained from this analysis is extendible to a set of $n \geq 3$ tasks as well.

Sequential Functional Specialists: This is our base case. Each task is performed by a distinct employee. Each employee operates out of a specialized functional department, where the existing information architecture ensures that they have swift access to the pertinent information required for their tasks. Employees have high expertise levels through repeated performing of the same task. They have little knowledge of the nature of tasks in the other departments. The workflow logic and the information each employee accesses are shown in Figure 2 (a).

Independent Multifunctional Generalists: Workers work independently and in parallel on entire jobs. Each worker receives half of the arriving jobs (at a rate of $\lambda/2$) and performs both tasks of a job. A worker may divert certain jobs to an expert to compensate for the loss in specialization when the worker leaves a functional environment. We model this fraction as β (the skill requirements). The expert completes the task, delaying completion and imposing the cost of her time on the firm. The workflow logic and the information access required is shown in Figure 2 (b).

Cross-Functional Team: The two employees work together on both tasks. Our observation (from studying such teams and from working in one at a reengineered corporation) has been that these teams reduce the knowledge gaps between specialists and improve the “assembly line” approach by enabling team members to understand the job specifications and purpose simultaneously and more clearly (through periodic team meetings, etc.). When the task sequence is fixed (as our model assumes) the possibility of parallel processing is eliminated. In any case, the co-ordination costs of processing interdependent tasks in parallel is high, and this prevents many teams from adopting this approach. We therefore model a team as processing the tasks one after the other. The delays from rereading specifications (which characterize a sequential system) are eliminated, and there are no losses from lack of specialization. The workflow logic and the information access required are shown in Figure 2 (c).

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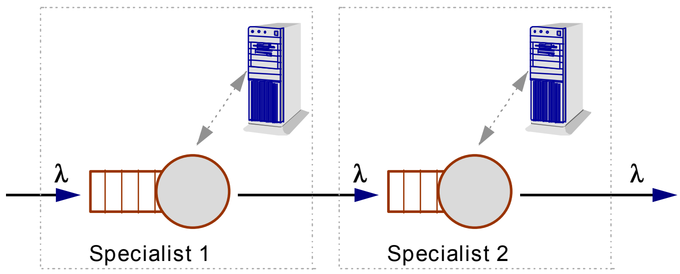
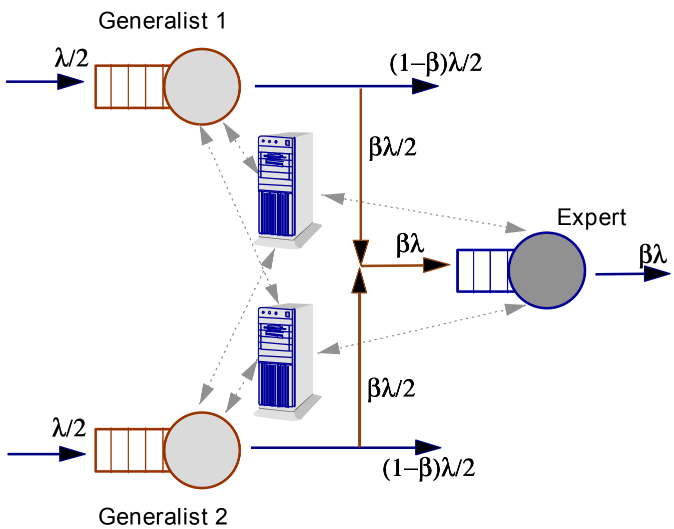
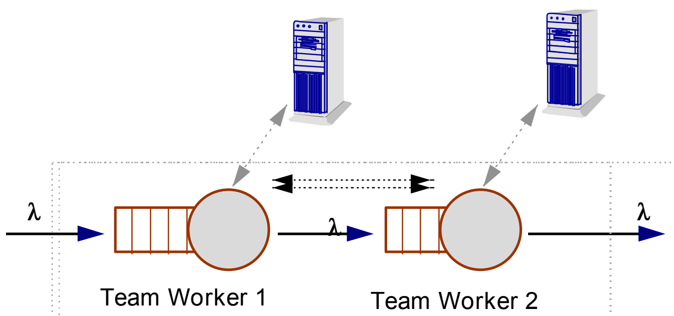
[1]Arguably, the different tasks in the job could require different levels of information. This is an example of task asymmetry. We address this situation in a related paper (Seidmann and Sundararajan 1996c); in this paper, we assume all tasks are equally information intensive. The same assumption holds for task complexity.



(a): Sequential Functional Specialists



(b): Parallel Multifunctional Generalists



(c): Cross-Functional Team

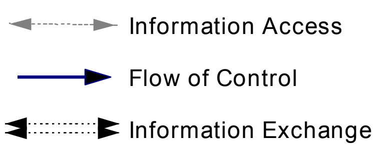


Figure 2. Different Forms of Job Control (Workflow Logic)

The choice of workflow logic, along with the job-specific parameters and the level of technology investment, determine the *process parameters*. Our model has four process parameters, σ, α, β, and τ, each corresponding to a particular job-specific parameter. In the absence of any additional technology support beyond that found in a functionally specialized organization, the value of these parameters is defined in Table 1.

Table 1. Values of Process Parameters for Different Workflow Logic

Workflow Logic	σ	α	β	τ
Sequential	σ_0	1	0	τ_0
Team	σ_0	α_0	0	τ_0
Generalist	σ_0	α_0	β_0	0

These values have not been assigned arbitrarily; there is a rationale behind each choice. For instance, if both tasks are performed by the same person (as is the case with generalists), then the level of task interdependence does not alter processing time (and hence the value of τ is 1 in this case, and τ_0 in the other two cases). Similarly, if the tasks are performed by specialists within their own departments, ready access to their departmental information systems ensures that the information intensity does not alter processing time (hence the value of α is 1); however, both a generalists and a team will need to access information from an external source, and hence the processing time of a task depends on information intensity.

The processing time of each task is assumed to be exponentially distributed.[2] The mean of this distribution is α/μ, which yields a processing rate μ/α. The rate is *divided by* σ if the task follows a handoff (due to rereading of specifications), and is *multiplied by* τ if the preceding task is done by a different person (due to task interdependence). In the case of multifunctional generalists, a fraction β of jobs go to an expert; any such job incurs an additional delay that is exponentially distributed with mean $\sigma/\tau\mu_e$, $\mu_e<\mu$ .The processing rates for each task under each form of workflow logic are summarized in Table 2.

Table 2. Values of Processing Rate per Task for Different Workflow Logic

Workflow logic	Task 1	Task 2
Sequential	$\frac{\mu}{\sigma}$	$\frac{\mu\tau}{\sigma}$
Team	$\frac{\mu}{\sigma\alpha}$	$\frac{\mu\tau}{\alpha}$
Generalist	$\frac{\mu}{\sigma\alpha}$	$\frac{\mu}{\alpha}$

[2]This distribution ensures that a precise analysis of queuing delays and effects is feasible.

The cycle time of a job in a process design is the sum of the expected queuing and processing time of the two tasks. In the absence of additional technology support, the following preliminary result can be derived. A proof of this result (and for results P2 through P4) are in our technical appendix.

P1: With all other parameters held constant, the consolidation of tasks (both tasks performed by the same person) reduces the processing time variability of a job. This reduces the expected queuing delays and improves process performance.

3.3 Incentives and Compensation

The workers in this process are compensated in two parts: a flat fee a per job completed, and a variable bonus ($b \times y$) where b is the bonus rate and y is the *performance measure*. We assume the performance measure to be *cycle time*; it is commonly used for time-sensitive processes and is more easily observable than other measures such as quality, customer satisfaction, etc. (in fact, it is commonly used as a surrogate for customer satisfaction, as a customer is more satisfied if the cycle time of her job is less). Besides, reengineered corporations often use other methods of control to ensure high quality work (such as quality training or the creation of a quality workplace) — evidently, these are more effective methods of ensuring quality. In the sequential case, we examine the cases where individual performance is observable, and also when it is not — the former can be made possible by technology that monitors when job control moves from one worker to the next. In the case of a generalist and a team, the workers are compensated based on cycle time of the entire job.

Depending on the contract offered, the workers choose a level of effort that determines the value of μ. The firm must choose the values of a and b that yield the optimal value of μ — this is an extremely difficult problem to solve (it is a principal-agent problem with one/two agents; the reader is referred to Holmstrom [1982, 1979] or Jensen and Meckling [1976] for more details on the agency problem and its analytical solutions). However, using Laplace transforms, we have closed form solutions for the optimal values of these parameters in each case.[3] Some preliminary results based on these solutions are given below.

P2: The use of technology that streamlines information flows (such as workflow automation systems) not only reduces cycle time through superior job control, but also reduces the cost of incentive compensation in sequential process designs.

P3: When workers are averse to risk,

(a) consolidating tasks using the multifunctional generalist approach reduces incentive compensation costs by reducing variability and increasing accountability, and

(b) incentive compensation costs are significantly higher for cross-functional teams than for multifunctional generalists.

3.4 The Role of Technology

We examine three of the performance-enhancing forms of technology discussed in section 2. Each of these technologies can alter the value of a process parameter. Our model addresses the following three key effects of technology on the performance of a worker: (i) information systems can reduce the processing time of a task by providing faster access to information; (ii) information systems can reduce the percentage of jobs diverted to an expert by expanding the skill set of generalists; (iii) information systems can reduce the delays caused by task interdependence by providing more efficient information sharing mechanisms.

The technology infrastructure of the process is represented as a vector (θ_1, θ_2, θ_3) as described below:

[3] In our technical appendix.

- θ_1 : Information-access-providing technology — shared databases, corporate-wide digital libraries or data warehouses that allow faster information access, and cross-functional information interchange. Increasing the level of θ_1 causes the value of α to decrease at an increasing rate (i.e., α is decreasing and convex[4] in θ_1). The rate at which α decreases in θ_1 is *higher* for a cross-functional team that for a generalist (generalists simultaneously access information from each system, which warrants a higher investment for the same performance returns).

- θ_2: Skill enhancing technology — for instance, expert systems, decision support systems, case-based reasoning systems, etc. Increasing the level of θ_2 causes the parameter β to decrease at an increasing rate (i.e., β is decreasing and convex in θ_2).

- θ_3 : Information sharing technology — for instance, a document sharing system, bulletin boards, groupware or discussion databases. Increasing the level of θ_3 causes the value of τ to increase at a decreasing rate (i.e., τ is increasing and concave in θ_3). The rate at which τ increases in θ_2 is *higher* for a cross-functional team that for a sequential system (such systems are less effective when implemented across functional boundaries). The magnitude of the impact of these technology variables on the corresponding parameters is what we term returns to technology.

The following results can be deduced from our models in sections 3.2 and 3.4.

P4: (a) A process incorporating sequential specialists is complemented by information sharing technology

(b) A process incorporating multifunctional generalists is complemented by skill enhancing and information access providing technology.

(c) A process incorporating cross-functional teams is complemented by information sharing and information-access-providing technology.

Consequently, processes for which each of the three forms of workflow logic is optimal will see an increased investment in the corresponding technologies.

3.5 The Interplay Between Technology, Incentives and Workflow Logic

The results *P1 through P4* are significant by themselves. *P1* shows that the consolidation of tasks not only eliminates rereading of specifications and delays due to task interdependence; it intrinsically reduces queue lengths by reducing processing time variability. As seen in *P3*, this has an additional consequence; since the cost of incentive based compensation is proportional to the variability in a performance measure, the cost of compensating workers goes down. Increased accountability from a single worker doing an entire job further reduces this cost. *P2* indicates that the popularity of workflow automation may not be solely due to reduced “disconnects” and better job control: it has implications for incentive compensation as well.

Numerical simulation using this analytical framework has yielded further insights,[5] which are summarized in Figures 3, 4 and 5. The text in each rectangle indicates the optimal process design. We first investigated the impact of workload on process design. We found that as workload increased, the generalist approach became more desirable, largely because of the reduction in processing time variability and the fact that a higher workload required higher processing rates (and therefore a process design

[4]The precise functional form we assume is $\alpha = 1+ (\alpha_0-1)\exp(-\alpha_1\theta_1)$, where α_1 measures the returns to information access technology and θ_1 is the technology level. α_1 is higher for a team than for a generalist. When $\theta_1 = 0$, $\alpha=\alpha_0$. As θ_1 increases, α approaches 1. Modifications of this functional form are used for parameters β and τ as well.

[5]A detailed discussion of the simulation and results is too lengthy to be included in the current paper. They are available from the authors upon request.

with lower costs for incentive compensation). However, at lower workloads, and with high technology returns, team based process designs without incentives dominated. This is partly a consequence of the better response that team based processes have to certain technologies. At low workloads and low technology returns, no conclusive patterns could be discerned.

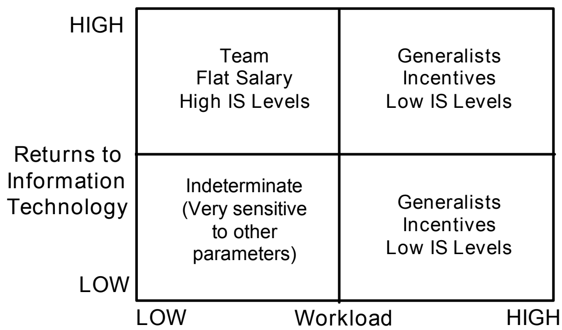


Figure 3. Impact of Information Technology Returns and Workload on Process Design

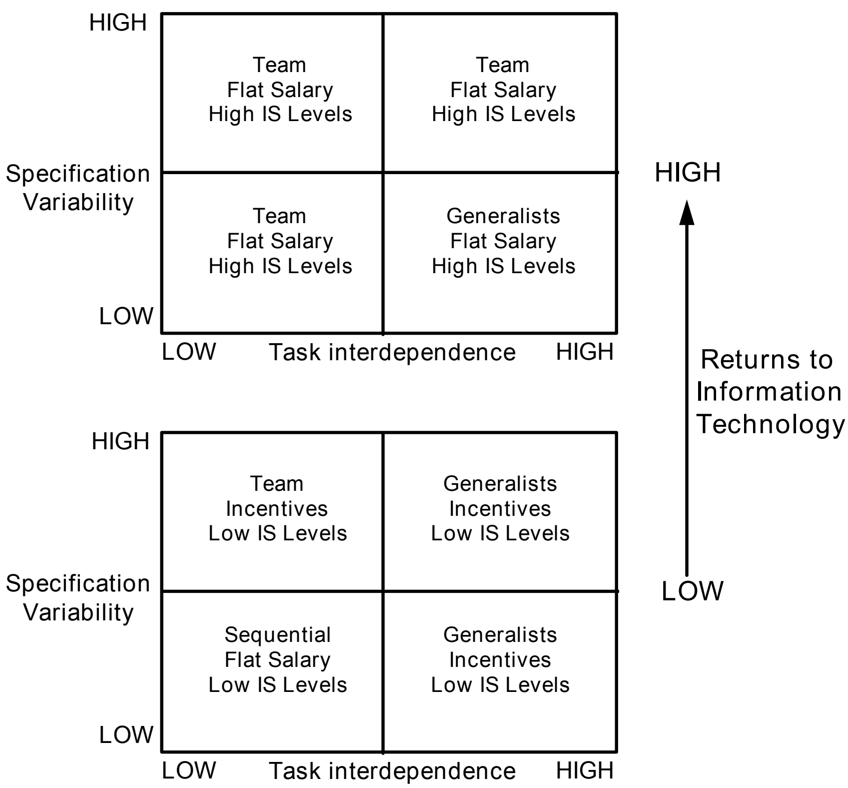


Figure 4. Impact of Specifications Variability and Task Interdependence on Process Design

Figure 4 summarizes the impact of specifications variability and task interdependence on process design. At low levels of task interdependence and specifications variability, and with low technology returns, sequential systems with flat salaries dominated, confirming intuition that routine, standard tasks with little overlap are ideally suited for the "assembly line" approach. As task interdependence grew, generalists with incentive compensation were the preferred choice — this is due to the low technology returns and the suitability of generalists for incentives. With low task interdependence and high specifications variability, teams dominated. An interesting pattern was revealed as we increased returns to technology. We found that incentive compensation was *substituted* by higher technology levels. Also, the superior response of teams to information sharing technology caused them to become the preferred choice in most cases. In the only exception (low variability, high task interdependence), generalists dominated; however, when technology levels went up, incentives were no longer cost effective.

The same broad patterns were observed in the impact of information intensity and skill requirements on process design (Figure 5). As returns to technology increased, incentive compensation was replaced by higher levels of technology, and team-based workflow logic became dominant. Generalists proved ideal for tasks with low information intensity and low complexity; the only exception to the substitution of incentives by technology was in this case, further confirming the suitability of this form of workflow logic for incentive compensation. At high levels of skill requirements and information intensity, functional specialists in sequence were dominant, replaced by teams only at high levels of technology returns.

Our model yields a number of interesting insights. We summarize these in the following section and also discuss our ongoing and future research in BPR and process design.

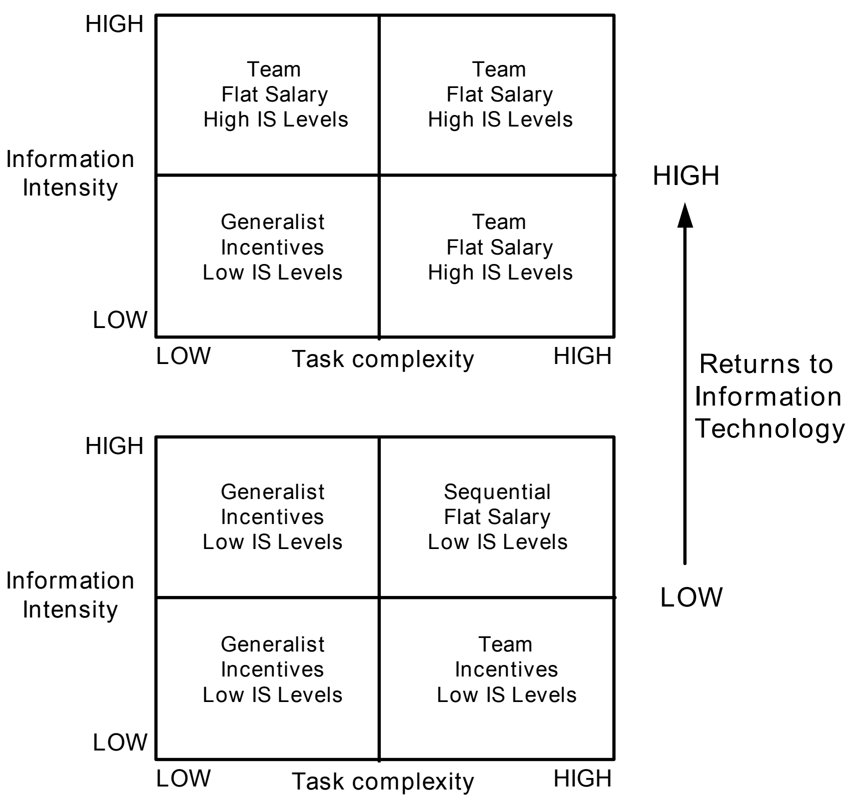


Figure 5. Impact of Information Intensity and Skill Requirements on Process Design

4. PRACTICAL IMPLICATIONS, INSIGHTS AND ONGOING RESEARCH

Managers who approach business process redesign have few solid guidelines when designing their new processes, or while targeting processes to redesign. The practical implications of our research are summarized below:

- When the tasks that constitute the process are relatively independent, do not vary much from customer to customer, or require high levels of expertise and access to specialized information, then a sequential process with a functional specialist and an activity based compensation scheme is optimal. Investing in high levels of new technology is probably not cost effective.

- If workloads in the current process are high and highly variable, then consolidating tasks and allocating multiple tasks to multifunctional generalists is the optimal decision. Incentive-based compensation is highly recommended. Task characteristics such as high interdependence, low complexity and low information intensity will suit such a process design ideally. Investment in high levels of new technology is not required in these cases, as the consolidation of tasks produces the same overall effect as, say, an information sharing system, and incentive schemes will result in sufficient increase in productivity. Skill-enhancing technology may be cost effective only if returns to technology are very high.

- When returns from technology investments in information accessibility, information sharing, etc., are high, then cross-functional teams are an ideal choice, as these technologies complement the workflow logic very well and can compensate for the lack of access to specialized information when workers are in a work environment that is not grouped by functional specialty. These teams are especially suitable when different customers have varying specifications and task consolidation is difficult due to high skill requirements and high information intensity. Incentives can work in some cases; however, since individual performance is difficult to measure and free riding may occur, investing in high technology levels that improve information access speeds and enhance information sharing are good substitutes for performance-based incentives.

Our ongoing research extends these results to more general settings involving tasks of different sizes and parameters (Seidmann and Sundararajan 1996a), and for processes with a higher number of tasks (Seidmann and Sundararajan 1996c). We also examine the competitive impact of decentralization of decision rights and its relation to task consolidation and customization (Seidmann and Sundararajan 1997). Another area we are currently examining concerns the changing nature of information ownership and the internal mechanisms that are required for decentralized access to specialized information by workers who no longer belong to functional departments or groups (Seidmann and Sundararajan 1996b).

We continue to closely follow the Fortune 50 corporation in its process reengineering efforts. Issues in change management are evidently an important part of its efforts, and we plan to address these in future research work. We also intend to analyze the role of inter-organizational information sharing technology on internal process design.

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TECHNICAL APPENDIX

Note:

- [*a*,*b*] denotes the closed interval *a* # *x* # *b*; (*a*,*b*) denotes the open interval *a* < *x* < *b* Similar interpretations hold for [*a*,*b*) and (*a*,*b*].

- The Laplace transform F*(s) of a function *f(.)* is defined as follows:

$$F^*(s) = \int_0^{\infty} e^{-sx} f(x)\,dx$$

For further information on the properties and use of this transform, the reader is referred to Smith (1966) or Watson (1981).

The proofs of P1 through P4 require a few preliminary lemmas. These are stated and proved below:

Lemma 1: The mean sojourn time g(x) in an M/M/1 queue is increasing and convex in the mean processing time x, for 0 # x < 1/8, where 8 is the arrival rate to the queue.

<u>Proof:</u> Let the arrival rate to the queue be λ and the processing rate be μ. Therefore, the mean processing time *x* = 1/μ. The mean sojourn time is $\frac{1}{\mu - \lambda}$ (see Kleinrock 1976 or Nelson 1995). Expressing this in terms of *x*, one gets:

$$g(x) = \frac{x}{1 - x\lambda}$$

It is easily verified that *gN(x)* > 0, *gO(x)* > 0∀*x* ∈ [0,1/λ)

Lemma 2: If g(.) is defined as in Lemma 1, then for any x in [*0,1/8*),

$$g(x\%g)\ \%\ g(x\&g)\ >\ 2g(x)\ œ\ x\ 0\ [0,\ \min 7\frac{1}{8}-x,\ x?)$$

<u>Proof:</u> As shown in Lemma 1, *g(.)* is convex in the specified region. The result is a property of a convex function. Limiting ϵ to $[0,\ \min\{\frac{1}{\lambda}-x,\ x\})$ ensures that *x*+ϵ and *x*-ϵ are in [0,1/λ)

Lemma 3: Let $\boldsymbol{X_1}$ *and* $\boldsymbol{X_2}$ *be two independent exponentially distributed random variables with parameters* μ_1 *and* μ_2*. If* $\boldsymbol{X}$ = $\boldsymbol{X_1}$ + $\boldsymbol{X_2}$*, then* $\boldsymbol{X}$ *has a mean* $\frac{1}{\mu_1} + \frac{1}{\mu_2}$ *and variance* $\frac{1}{\mu_1^2} + \frac{1}{\mu_2^2}$.

<u>Proof:</u> The first part is immediately obvious, since the mean of the sum of two random variables is the sum of their means. Denote the density functions of **X**, $\mathbf{X_1}$ and $\mathbf{X_2}$ as *f(.)*, $f_1(.)$ *and* $f_2(.)$, and their corresponding Laplace transforms as F*(s), F_1*(s) and F_2*(s). Since $\mathbf{X} = \mathbf{X_1} + \mathbf{X_2}$ it follows that $f(x) = f_1(x) * f_2(x)$, where * denotes the convolution operator (see Ross 1980 eq. 5.9 for a proof of this result). Hence, from the properties of the Laplace transform, $F^*(s) = F_1^*(s)F_2^*(s)$ (see Smith 1966, Chapter 5, or Watson 1981, P.1.2.2, for the proof of this, other properties of the Laplace transform, and the Laplace transform pairs used subsequently). However,

$F_1^*(s) = \dfrac{\mu_1}{\mu_1 + s}$ and $F_2^*(s) = \dfrac{\mu_2}{\mu_2 + s}$. Hence, $F^*(s) = \dfrac{\mu_1\mu_2}{(\mu_1 + s)(\mu_2 + s)}$.

The variance of a random variable **X** can be expressed as $E(\mathbf{X}^2) - [E(\mathbf{X})]^2$. As mentioned earlier, $E(\mathbf{X}) = \dfrac{1}{\mu_1} + \dfrac{1}{\mu_2}$. Also,

as seen in Nelson (1995) eq. 5.60,

$$E(\mathbf{X}^2) = \lim_{s\to 0}\frac{\partial^2 F*(s)}{\partial s^2}$$

$$= \lim_{s\to 0}\frac{\mu_1\mu_2}{(\mu_1+s)(\mu_2+s)}\left[\frac{1}{(\mu_1+s)^2}+\frac{1}{(\mu_2+s)^2}\right]+\frac{\mu_1\mu_2}{(\mu_1+s)(\mu_2+s)}\left[\frac{1}{(\mu_1+s)}+\frac{1}{(\mu_2+s)}\right]^2$$

$$= \frac{\mu_1\mu_2}{(\mu_1)(\mu_2)}\left[\frac{1}{(\mu_1)^2}+\frac{1}{(\mu_2)^2}\right]+\frac{\mu_1\mu_2}{(\mu_1)(\mu_2)}\left[\frac{1}{(\mu_1)}+\frac{1}{(\mu_2)}\right]^2$$

$$= \left[\frac{1}{(\mu_1)^2}+\frac{1}{(\mu_2)^2}\right]+\left[\frac{1}{\mu_1}+\frac{1}{\mu_2}\right]^2$$

Hence, $\mathrm{var}(\mathbf{X}) = \left[\dfrac{1}{(\mu_1)^2}+\dfrac{1}{(\mu_2)^2}\right]$

Lemma 4 (P-K mean value formula): If the arrival process to a queue is Poisson with parameter 8, and its service time has a mean 8/D and variance F^2 then the mean sojourn time in the queue is given by $W_S = \dfrac{\rho}{\lambda} + \dfrac{\rho^2 + \lambda^2\sigma^2}{2\lambda(1-\rho)}$

See Kleinrock (1976) or Nelson (1995) for a discussion of this result, which is known as the Pollaczek-Khinchin mean value formula.

Proof of P1:

The proof is constructed as follows. We first show that the sojourn time of a two stage sequential system with processing rates μ_1 and μ_2 is weakly lower than that of a single consolidated *M/M/1* queuing system with processing rate $\left[\frac{\mu_1\mu_2}{(\mu_1+\mu_2)}\right]$, and that they are equal if and only if $\mu_1 = \mu_2$ (this is in Part 1 of the proof). We than show that the sojourn time of the generalist's queue is *strictly lower* than that of a single consolidated *M/M/1* queuing system with processing rate $\left[\frac{\mu_1\mu_2}{(\mu_1+\mu_2)}\right]$, and that this lowered sojourn time is due to lower processing time variability (this is in Part 2). This proves the result for $\tau = 1$. The result is further strengthened if τ takes any other value in [0, 1). This approach eliminates the need for complicated (and non-intuitive) algebra.

Part 1: Consider a sequential system which consists of two *M/M/1* queues with arrival rate λ and processing rates μ_1 and μ_2 respectively. Assume without loss of generality that $\mu_1 < \mu_2$. Let $t_1 = 1/\mu_1$ and $t_2 = 1/\mu_2$ be the mean processing times of each server. Also consider a single *M/M/1* queue with arrival rate $\lambda/2$ and processing rate $\left[\frac{\mu_1\mu_2}{(\mu_1+\mu_2)}\right]$. Denote its mean sojourn time as *S*. $S = \dfrac{1}{[\frac{\mu_1\mu_2}{(\mu_1+\mu_2)} - \frac{\lambda}{2}]} = \dfrac{2}{\frac{2\mu_1\mu_2}{(\mu_1+\mu_2)} - \lambda}$.

Let *g(x)* denote the mean sojourn time in an *M/M/1* queue with arrival rate λ and mean processing time *x* (as in Lemma 1 and 2). It is easily seen that $S = 2g(t)$ where t = $\left[\frac{(\mu_1+\mu_2)}{2\mu_1\mu_2}\right]$.

Now, the total mean sojourn time in the sequential system is $g(t_1) + g(t_2)$. However, $t_1 - t = t - t_2 = \left[\frac{(\mu_2-\mu_1)}{2\mu_1\mu_2}\right]$. If $\epsilon = \left[\frac{(\mu_2-\mu_1)}{2\mu_1\mu_2}\right]$, then $t_1 = t+\epsilon$ and $t_2 = t - \epsilon$. Setting $x = t$ and $\epsilon = \left[\frac{(\mu_2-\mu_1)}{2\mu_1\mu_2}\right]$ in Lemma 2 proves the first part of this proposition.

Part 2: Now consider the same consolidated *M/M/1* queue compared to our generalist. Both have the same arrival rate λ and mean processing time $\frac{1}{\mu_1} + \frac{1}{\mu_2}$. The variance of processing time of the server in the *M/M/1* is $\dfrac{1}{[\frac{\mu_1\mu_2}{(\mu_1+\mu_2)}]^2} = \frac{1}{\mu_1^2} + \frac{1}{\mu_2^2} + \frac{2}{\mu_1\mu_2}$. The variance of the processing time of the system with the generalist is $\frac{1}{\mu_1^2} + \frac{1}{\mu_2^2}$ (from Lemma 3). It is evident from Lemma 4 that the mean sojourn time is increasing in variance of the processing time at the server. Hence the sojourn time of the generalist is strictly lower, as the processing time variance is strictly lower.

Substituting $\mu_1 = \mu/\sigma\alpha$ and $\mu_2 = \mu/\alpha$ proves P1 for $\tau = 1$.

If $\tau < 1$, this reduces the processing rate of the second team member, thus increasing the net sojourn time in the sequential system. Hence as τ reduces, the result strengthens.

Characterization of the optimal values of *a* and *b*.

Before P2 and P3 are proved, we describe the solution technique for the optimal contract (*a*,*b*). Knowledge of the basic concepts of the principal agent problem is assumed (the reader is referred to Mas-Colell, Whinston and Green 1995, Chapter 14, for a discussion of this problem and some commonly used results).

In our model, the principal (or manager) attempts to minimize the total cost per job by choosing a particular workflow logic, and by inducing either a low or high effort level from the workers in the process. The assumptions of the model (risk averse workers, risk neutral principal, non-additively separable utility function) are at least as general (if not more) as those made in most work done in this area. The additional notation used is summarized below:

$U(x) = -e^{-\eta x}$: Utility function of the workers in the process; the argument is monetary compensation[6]

$e \in \{e_L, e_H\}$: Effort exerted by workers.
μ_L, μ_H: Base processing rates corresponding to low and high effort levels; $\mu_L < \mu_H$
$c(e_i) = c_i$: Cost of exerting low or high effort measured in monetary units; $c_L < c_H$
$f(\cdot|e_i)$: Density function of cycle time if workers work at effort level e_i
$F^*(s|e_i)$: Laplace transform of $f(\cdot|e_i)$
U_0: Reservation utility of the workers (the minimum utility they need to participate)
c_D: Delay cost rate (measures the benefits to the firm if the process cycle time reduces by one time unit)
$T_S(e_i)$: Expected cycle time of the process if workers work at effort level e_i

The principal's problem can be stated as follows:

$$\min_{a,b} c_D T_S(e^*) + 2a + 2bT_S(e^*)$$
$$\text{s.t.}$$
$$\int_0^\infty U(a + by - c(e^*))\, f(y|e^*)dy \ge U_0$$
$$e^* = \arg\max_{e \in \{e_L, e_H\}} \int_0^\infty U(a + by - c(e^*))\, f(y|e^*)dy$$

The objective function is the sum of the expected delay costs and compensation costs. The first constraint ensures that the workers get their minimum reservation utility. The second constraint ensures that, given the contract (*a*,*b*), the effort level *e** induced provides the workers with the maximum possible utility (otherwise they would choose an effort level that makes them better off).

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[6]This is a very commonly used utility function, which has the property of being of constant absolute risk aversion (CARA). It has been used in many influential papers, including Holmstrom and Milgrom (1987).

The expression for $T_S(.)$ is easily derived (all our queues have well defined, closed form expressions for their expected cycle time). Given the structure of our utility function, the problem reduces to:

$$\begin{aligned}
&\min_{a,b} c_D T_S(e^*) + 2a + 2bT_S(e^*) \\
&\text{s.t.} \\
&\int_0^\infty -e^{(a+by-c(e^*))} f(y|e^*)dy \geq U_0 \\
&e^* = \underset{e\in\{e_L,e_H\}}{\arg\max} \int_0^\infty -e^{(a+by-c(e^*))} f(y|e^*)dy
\end{aligned}$$

However, from the definition of the Laplace transform, and the fact that the principal's costs are strictly increasing in *a*, this can be expressed as:

$$\begin{aligned}
&\min_{a,b} c_D T_S(e^*) + 2a + 2bT_S(e^*) \\
&\text{s.t.} \\
&-e^{\eta(c(e^*)-a)} F^*(\eta b|e^*) = U_0 \qquad (1) \\
&e^* = \underset{e\in\{e_L,e_H\}}{\arg\min}\ e^{\eta c(e^*)} F^*(\eta b|e^*) \qquad (2)
\end{aligned}$$

Solving the first constraint yields the value of *a* in terms of known parameters and *b*. Since the Laplace transforms of the cycle times of our queues are quadratic in *b* at worst, the second constraint yields a quadratic equation in *b* which can be solved, yielding an expression for *b* in terms of known parameters. Choosing between inducing a low or high effort level (by calculating the relevant delay and compensation costs) solves the principal's problem.

As an illustration of our solution technique, consider the sequential case where there is a workflow automation system that enables the principal to determine the cycle time of each task. She therefore can contract individually with each agent, and minimize costs for each task (the minimum cost process will be a combination of the minimum cost cycle times). The algebra for the contract with the first agent is shown below:

The task cycle time is exponentially distributed with parameter μ/σ. The expected cycle time $T_S(e_i) = \dfrac{1}{\frac{\mu}{\sigma}-\lambda}$, and the Laplace transform of the density function of cycle time is $F^*(s|e_i) = \dfrac{\frac{\mu_i}{\sigma}-\lambda}{s+\frac{\mu_i}{\sigma}-\lambda} = \dfrac{\mu_i - \sigma\lambda}{\sigma s + \mu_i - \sigma\lambda}$.

The principal must choose between inducing effort level e_H and effort level e_L, and will choose to induce that effort level that minimizes total costs. In order to compute these costs, we first solve for the contract that induces each of these effort levels.

<u>Contract that induces effort level e_H:</u>

Constraint (1) reduces to:

$e^{-\eta a}.e^{\eta c_H}.F*(\eta b|e_H)=U_0$, which solves to:

$$a=c_H-\frac{1}{\eta}\log\left[\frac{-U_0(\sigma\eta b+\mu_H-\sigma\lambda)}{\mu_H-\sigma\lambda}\right]$$

Constraint (2) reduces to:

$$e^{\eta c_H}\frac{\mu_H-\sigma\lambda}{\sigma\eta b+\mu_H-\sigma\lambda}\leq e^{\eta c_L}\frac{\mu_L-\sigma\lambda}{\sigma\eta b+\mu_L-\sigma\lambda}$$

The lowest cost solution is at equality. This solves to:

$$e^{\eta(c_H-c_L)}(\mu_H-\sigma\lambda)(\sigma\eta b+\mu_L-\sigma\lambda)=(\sigma\eta b+\mu_H-\sigma\lambda)(\mu_L-\sigma\lambda)$$

or $$b=(1-\frac{e^{\eta(c_H-c_L)})(\mu_H-\sigma\lambda)(\mu_L-\sigma\lambda)}{\sigma\eta[(e^{\eta(c_H-c_L)}(\mu_H-\sigma\lambda))-(\mu_L-\sigma\lambda)]}$$

<u>Contract that induces effort level e_L:</u>

It is easy to see that *b* = 0 for this contract (see Mas-Colell, Whinston and Green 1995, Chapter 14, for a discussion of this). The value of *a* is that which gives the worker reservation utility, which, from constraint (1) is

$$a=c_L-\frac{1}{\eta}\log\left[\frac{-U_0(\sigma\eta b+\mu_L-\sigma\lambda)}{\mu_L-\sigma\lambda}\right]$$

The principal chooses the contract that minimizes total cost — since the delay costs and compensation costs are explicitly known for each effort level, all that has to be done is to decide on the effort level that has the lowest total cost to the principal, and induce that with its corresponding contract. Similar analysis is used for the other cases.

Proof of P2:

When a workflow automation system is used, the manager or firm owner can observe the individual cycle time of each agent in the process, as opposed to just the total cycle time. This enables superior contracting with each worker based on the specific performance of that worker. It can be shown explicitly that compensation costs go down by solving for *a* and *b* in each case. However, that is unnecessary, as Proposition 3 of Holmstrom (1979) is applicable here. This is because, among other things, a workflow automation system enables the principal to track precisely when a job enters and leaves a worker's queue. Therefore, when the workflow automation system is used, the principal has an additional signal of performance (the task time of each worker), and this signal is informative (it adds to the estimate of the effort level of the worker). The proposition quoted proves that any signal of this kind causes the principal to be strictly better off, by reducing agency costs (or in our case, compensation costs).

The result that delay costs are reduced due to better streamlining of work flows is simple to understand. Suppose that there exists a delay *D* between the time the first worker finishes task 1 of a job and the second worker is aware that the job is ready for task 2 (i.e., a delay *D* between the time worker 1 finishes, and the job enters the queue of worker 2). This will cause an additional delay if worker 2's queue is empty at any time during this period. As long as $\mu\tau/\sigma > \lambda$, there is a positive finite probability that this is true. Hence, eliminating this delay causes a strict reduction in the total cycle time of the process if $\mu\tau/\sigma > \lambda$. However, $\mu\tau/\sigma \leq \lambda$ is not possible, since this causes the cycle time of the process to be infinite. Therefore, the introduction of a workflow automation system that eliminates these delays will cause a strict reduction in the processing cost of a job.

Proof of P3:

(a) The reduction in compensation costs when the process design uses multi-functional generalists comes from two sources. Firstly, the cycle time of a job is a superior signal of each worker's performance. When the workers work in a team, or in sequence, the cycle time of the job measures the effort levels of *both workers*. Consolidating these tasks eliminates the effect of free riding (see Holmstrom 1982) and therefore eliminates the loss in welfare from free riding. This reduction in agency costs accrues to the principal, since the agents have to be paid less than before to get the same utility U_0.

The second source of reduction in costs is due to the reduced variability in cycle time. As seen in Lemma 3 and P1, when tasks are consolidated, the variability in processing time and thus the variance of cycle time. This implies that under a particular compensation scheme, the agent exerts a higher effort, or alternatively, the payoff required to induce the high level of effort is lower, as long as $\eta > 0$ (i.e., the workers are strictly risk averse). Further discussion of result of this kind can be found in Meyers and Ormiston (1983, 1985) and in Dionne, Eeckhoudt and Gollier (1993). Another way of proving this is by using the argument that when the variance of a performance measure reduces, the risk premium that has to be paid to the agents reduces, thus reducing the compensation costs of the principal.

(b) As seen in our model, cross functional teams have lower accountability (the observable measure of cycle time is a less informative signal of any specific worker's effort level, as compared to the case of a generalist), and higher variance in cycle time (the performance measure). Therefore, as discussed in P3 (a) above, each of these two effects causes an increase in compensation costs.

Proof of P4:

Recall the following table (Table 2) from the main paper:

Workflow logic	**Task 1**	**Task 2**
Sequential	$\frac{\mu}{\sigma}$	$\frac{\mu\tau}{\sigma}$
Team	$\frac{\mu}{\sigma\alpha}$	$\frac{\mu\tau}{\alpha}$
Generalist	$\frac{\mu}{\sigma\alpha}$	$\frac{\mu}{\alpha}$

(a) The net cycle time of the process in the case of sequential specialists is $\frac{1}{\frac{\mu}{\sigma}-\lambda}+\frac{1}{\frac{\mu\tau}{\sigma}-\lambda}=\frac{\sigma}{\mu-\sigma\lambda}+\frac{\sigma}{\mu\tau-\sigma\lambda}$ which is decreasing in τ. Since τ is increasing in θ_3, this implies that cycle time is decreasing in θ_3. However, since process costs are increasing in cycle time, this implies that they are decreasing in θ_3; hence an increase in θ_3 (the level of information sharing technology) causes process costs to reduce.

(b) The expected cycle time of a job in a process which uses multi-functional generalists is $\frac{1}{\frac{\mu}{\sigma\alpha}-\lambda}+\frac{1}{\frac{\mu}{\alpha}-\lambda}+\beta(\frac{1}{\mu_e-\beta\lambda})=\frac{\sigma\alpha}{\mu-\sigma\alpha\lambda}+\frac{\alpha}{\mu-\alpha\lambda}+\frac{\beta}{\mu_e-\beta\lambda}$ which is increasing in both α and β. Since α is decreasing in θ_1, β is decreasing in θ_2, and process cost is increasing in cycle time, this shows that process cost is decreasing in both θ_1 and θ_2.

(c) The expected cycle time of a job in a process which uses a cross functional team is $\frac{1}{\frac{\mu}{\sigma\alpha}-\lambda}+\frac{1}{\frac{\mu\tau}{\alpha}-\lambda}=\frac{\sigma\alpha}{\mu-\sigma\alpha\lambda}+\frac{\alpha}{\mu\tau-\alpha\lambda}$ which is increasing in α and decreasing in τ. Since α is increasing in θ_1, τ is decreasing in θ_3, and process cost is increasing in cycle time, this shows that process cost is decreasing in θ_1 and θ_3.