White Collar Workforce Management: An Operations-Oriented Survey

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Abstract

Although white collar work is of vast importance to the economy, the Operations Management (OM) literature has focused largely on traditional blue collar work. In an effort to stimulate more OM research into the design, control and management of white collar work systems, this paper provides a systematic review of disparate streams of research relevant to understanding white collar work from an operations perspective. Our review classifies research according to its relevance to white collar work at individual, team and organizational levels. By examining the literature in the context of this framework, we identify gaps in our understanding of white collar work which suggest promising research directions.

Keywords: white collar work, operations management, survey

1 Introduction

Operations Management (OM) is concerned with the processes involved in delivering goods and services to customers (Hopp and Spearman 2000, Shim and Siegel 1999). At the core of many of these processes is the workforce. Indeed, the field of OM has its roots in the labor efficiency studies of Frederick W. Taylor and other champions of the Scientific Management movement of the early twentieth century. Because these early studies focused on manufacturing and other physical tasks, the OM field developed a tradition of studying "blue collar" systems. The dramatic improvements in direct labor productivity over the past several decades suggest that this line of research has been highly effective.

However, in recent years, the U.S. economy has steadily shifted toward service and professional "white collar" work, with such workers now constituting 34 percent of the workforce according to the Bureau of Labor Statistics (BLS) (Davenport et al. 2002). Furthermore, according to the BLS, workers in "management, business, and financial occupations" and in "professional and related occupations" will increase by 14.4% and 21.2%, respectively, from 2004 to 2014, which ranks them as the 3rd and 1st fastest growing occupation categories [1]. This trend suggests that future economic growth will depend

[1] http://www.bls.gov/emp/emptab1.htm

much more on improving productivity of workers in white collar work settings than on achieving further improvements in blue collar productivity.

Despite the obvious importance of white collar work to the economy, it is much less understood in an operations sense than is blue collar work. Well-known principles of bottleneck behavior, task sequencing, line balancing, variability buffering and many others (Askin and Goldberg 2002, Hopp and Spearman 2000) help us evaluate, improve and design blue collar work work systems. But in white collar work systems, where tasks are less precisely defined and controlled than in blue collar systems, we do not yet have principles for guiding operations decisions. Fundamental questions remain unanswered. For example: What is the bottleneck of a white collar work system? What are appropriate measures of productivity? How does collaboration affect performance? To answer these and many other questions, we need a science of white collar workforce operations.

A variety of fields, including Operations Management, Economics, Sociology, Marketing, and Organizational Behavior have produced streams of research relevant to white collar work. While these have yet to coalesce into a coherent science, research in these fields has yielded useful insights. In this paper, we survey a wide range of research that offers promise for understanding the operations of white collar work. Our objectives are to bring together these disparate threads, provide a framework for organizing them, and identify needs and opportunities for developing a science of white collar work.

2 Definition of White Collar Work

To achieve these objectives we must first define what we mean by white collar work. Historically, the term "white collar" has been used loosely to refer to salaried office workers, in contrast with hourly "blue collar" manual laborers (Shirai 1983).[2] Sometimes "white collar" refers to the rank or social status of the worker. For example, answer.com defines white collar worker as "office worker in professional, managerial, or administrative position. Such workers typically wear shirts with white collars.[3]" Other definitions of white and blue collar work are based on whether the worker performs manual work. For example, Prandy et al. (1982) used the term "white-collar" to refer to non-manual labor, e.g., supervisors, clerks, professionals, and senior managers. Still other definition of white collar work focused on job categories. For example, Coates (1986) divided white collar work into three categories: clerical, professional, and managerial. Because of the nature of the work, some scholars have equated

[2]The root of these terms is the color of the shirts worn by the workers; office workers traditionally wore white shirts, while laborers wore work shirts that were often blue. Relaxation of professional dress codes and colorful trends in fashion have rendered these terms somewhat anachronistic.

[3]See http://www.answers.com/topic/white-collar-worker.

white collar workers with knowledge workers (McNamar 1973, Ramirez and Nembhard 2004). In this vein, Stamp (1995) summarized eight important aspects of white collar work: "Surfacing and aligning values and vision," "Thinking strategically," "Focusing key resources, at the same time maintaining flexibility," "Managing priorities," "Measuring performance," "Accepting ownership, responsibility and accountability," "Influencing, while maintaining interpersonal awareness," and "Continually improving people, products and processes."

Although these definitions give a general sense of what constitutes white collar work and how it differs from blue collar work, they do not provide a precise or consistent statement that we can use to focus research into the operations of white collar work. For example, Coates (1986) classifies clerical work, such as typing, as white collar work. However, typing does not have any of the eight features of white collar work as defined in Stamp (1995). Moreover, from an operations perspective, typing has much more in common with machining (commonly thought of as "blue collar") than with management (commonly thought of as "white collar"). To study the operations aspects of white collar work, we need a definition that distinguishes white and blue collar work in operationally meaningful ways.

Some researchers have argued that the old white-blue work dichotomy is obsolete (Barley and Kunda 2001, Zuboff 1988). While we agree that management practices, such as empowerment and self-directed teams may indeed blur the distinction between white and blue collar work, we believe there remains a fundamental distinction between the two types of work at the *task level*. That is, we focus on the tasks involved in the work, (e.g., financial consulting, operating machine tool) rather than on the workers (e.g., financial advisors, machine tool operators).

Viewed in this way, someone we customarily think of as blue collar worker may perform white collar tasks (e.g., a machinist brainstorms methods for improving the yield of his operation). Conversely, some we normally think of as a white collar worker may perform blue collar tasks (e.g., a professor makes her own photocopies). Hopp and Van Oyen (2004) defined a task as a *process* that brings together *labor*, *entities* and *resources* to accomplish a specified objective. In this highly general definition, labor refers to workers (e.g, machinist, doctor, cashier, banker). An entity represents the job being worked on (e.g., part, patient, customer, financial transaction). Resources include anything used by labor to carry out the activity of the task, such as equipment (e.g., machines, computers), technology (e.g., algorithms, infrastructure systems), and intellectual property (e.g., books, reports, outside expertise).

A task is defined by the three element - labor, entities and resources - as well as the processes that describe how they are brought together. For our purposes, whether a task is classified as blue or white collar depends on how it is characterized along two dimensions:

1. *Intellectual vs. Physical:* White collar tasks mainly involve using knowledge as a dominant element in generating ideas, processes or solutions (Davenport and Prusak 2002), while blue collar tasks mainly involve physical labor to perform a mechanical transformation of a material object. For example, data analysis requires the worker to select and/or develop appropriate models specific to each different case by drawing on his/her expertise, statistical knowledge, and prior experiences. In contrast, moving a batch from one machine to another in shop floor requires physical effort but demand a low level of knowledge.

2. *Creative vs. Routine:* White collar tasks mainly involve generation of novel solutions or combination of previously unrelated ideas (Davenport and Prusak 2002, Perry-Smith and Shalley 2003, Shalley 1995), while blue collar tasks consist primarily of repetitive application of known methods to familiar situations. For example, to formulate a new drug, researchers must design new experiments based on their domain knowledge and creative thinking. Upon completion of each experiment, a new set of data is collected, analyzed, and used to direct new experiments. In contrast, sewing involves repetition of the same actions on each garment. Because the required actions are repetitive in nature, clear procedures, which govern the work, can be specified in advance of the arrival of the work.

To provide a reasonable correspondence with the colloquial use of the terms "blue collar" and "white collar," we define a blue collar task to be one that is both physical and routine. Any task that is either intellectual or creative, we define as white collar. We illustrate this definition in Figure 1, with some examples of types of work characterized by different positions in this two dimensional space.

It is important to point out that, under this definition, there is no such thing as a pure blue collar or pure white collar job (Ramirez and Nembhard 2004). For example, driving a lift truck to move heavy parts from one part of the factory to another is generally considered to be blue collar work. However, while driving a lift truck is mainly physical and routine, the driver must sometimes use his creativity to figure out how to efficiently load and unload large items with irregular shapes. So we classify the task of driving parts from point A to point B as a blue collar task, but classify the task of finding a way to transport new or unusual parts as a white collar task. Under our definition, all workers, whether they are conventionally thought of as white or blue collar, do both white and blue collar work (Drucker 1999). Since, as OM scholars, we are interested in the efficiency of operations, we are more concerned with classifying and analyzing tasks than with classifying people. Models of white collar tasks are the foundation for a science of white collar work.

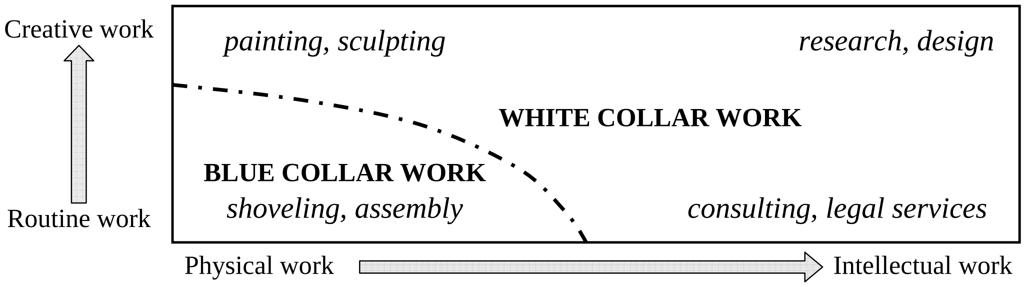

Figure 1: White Collar Work vs. Blue Collar Work

The above definition raises the question of how white collar work is related to service work. One might be tempted to classify all service work as white collar work because it does not involve heavy physical activity. For example, the tasks carried out by a bank teller do not involve significant work in the physics sense. But, since these tasks are highly routine, they are neither intellectual nor creative. Hence, in our framework, tasks such as counting money, entering transactions in a bank book, cashing checks, etc., are predominantly physical and routine and therefore qualify as blue collar work. From an operations standpoint, the work of a bank teller has far more in common with that of an assembly line worker than it does with that of a lawyer or consultant.

A second distinction that is worth making is that between white collar work and knowledge work (Davenport et al. 2002). Roughly speaking, knowledge work corresponds to the right half of Figure 1, while production work corresponds to the left half. Any task with a high intellectual content qualifies as knowledge work. Under our definition, this also makes it white collar work. But there are also white collar tasks that are physical and not intellectual in nature. For instance, but they require a high level of creativity and so qualify as white collar work in our framework. Again, the work of a surgeon has more in common with that of a lawyer than that of a janitor, so it makes sense to include surgical tasks in the white collar category.

To build toward a science of white collar work, we follow the standard OM approach used to model blue collar systems by starting with a simple structures, such as single-class job, single-server (e.g., simple produce-to-order system) and extending the analysis to more complex structures, such as multi-class, multiple-server systems. To do this, we divide our taxonomy of white collar research into work at the *individual*, *group*, and *organization* levels. This allows us to compare and contrast issues in white and blue collar work systems. In Section 3, 4, and 5, we propose generic models for representing white collar work at individual, group, and organization level and then discuss research relevant to elements of the models. By noting which aspects of the generic models have not been well studied in the literature, we are able to suggest promising avenues of future research in Section 6. We summarize our overall conclusions in Section 7.

Covering all aspects of white collar work systems, which could include issues as diverse as public policy, education, urban development, etc., is impossible. So we restrict our goals to: (1) identifying key streams of research that are relevant to an operations understanding of white collar work, and (2) highlighting important papers within each stream that will help direct OM researchers to useful sources of literature for understanding white collar work.

3 White Collar Work at the Individual Level

The simplest context in which to study white collar work is that of a single person carrying out tasks independently. Examples include a doctor treating a patient, a scientist writing a research paper and a lawyer preparing a case. Although many studies in the OM literature have addressed systems that involve individual work (Buzacott and Shanthikumar 1993, Hopp and Spearman 2000), these often implicitly combine workers with equipment by assuming "workers are not a major factor", "people (i.e., workers) are deterministic and predictable," "workers are stationary," and "workers are emotionless" (Boudreau et al. 2003). While such assumptions may be oversimplifications in blue collar settings, they are completely unrealistic in white collar systems because white collar tasks involve knowledge and creativity, as well as human characteristics like learning, emotion and judgment. So representing these is a key step in modeling white collar work.

3.1 A Basic Model

To provide a conceptual framework for representing individual work, we return to the basic representation of a task in Hopp and Van Oyen (2004), which depicts tasks in terms of labor, entities and resources. Since we are talking about individual work, the labor in these systems consists of a single worker. The entities are the logical triggers of tasks. These could be outside requests (e.g., demands from the boss, customer calls for service) or internally generated items (e.g., an idea for a research paper, a plan for improving a system). The resources could include a broad range of physical (e.g., pen, paper, computer) and informational (e.g., books, web sites, personal knowledge, outside expertise) elements. Finally, a fourth element that describes an individual work system is the set of processes that govern how the labor, entities and resources are brought together to complete tasks. These could include sequencing/scheduling rules, incentive policies and a variety of management directives. We illustrate this individual work system schematically in Figure 2.

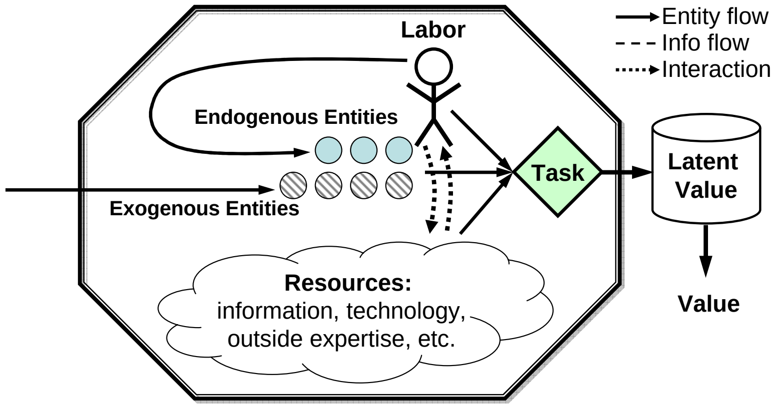

Figure 2: White Collar Work at the Individual Level

Note that this model highlights both some similarities and some key differences between white and blue collar work. Similarities stem from the fact that both systems exhibit queueing behavior, in which entities pile up awaiting attention from a worker with finite capacity. This means that variability and high utilization will cause congestion (see Hopp and Spearman (2000) for a discussion). But there are important differences, including:

1. By our definition of white collar work, the tasks themselves are of an intellectual and/or creative nature. Workers must accumulate sufficient domain knowledge before they can carry out tasks. For example, a risk analyst must master a body of knowledge in order to understand, formulate, and analyze risk problems. Moreover, white collar tasks rarely repeat themselves, which implies that creativity is often important in white collar work. For example, in addition to assessing risks in familiar settings, a risk analyst must evaluate new risk scenarios, which requires a certain amount of creativity.

2. White collar work systems rely more heavily on knowledge-based resources. While blue collar tasks may require informational inputs (e.g., an instruction sheet showing how parts should be assembled), the standardized nature of the work implies that these inputs will be relatively simple. In contrast, white collar tasks, which involve a higher level of intellectual complexity, may rely on general information that must be processed and synthesized by the worker. For

instance, a lawyer preparing a case may have to cull through a vast backlog of precedents and select those relevant to the case at hand.

3. Learning is slower and more central in white collar systems. The complexity of the resources and the novelty of the tasks mean that white collar workers often have more to learn than blue collar workers. While some models of blue collar work systems involve learning (e.g., by representing workers as growing more productive over time), such learning dynamics are even more important in white collar work systems. Moreover, since the skills involved may be diverse, this learning may be correlated with other things beyond time in the position.

4. Measurement of output is more difficult in white collar work systems. In blue collar systems the outputs are primarily physical (e.g., completed assemblies, cleaned hotel rooms, painted houses). As such, their value can be measured immediately upon completion of a task. For example, a machining operation could go directly to a test station where it is checked for quality, so that the value created by the machinist could be measured as the rate of acceptable parts produced per day. But in white collar systems, the outputs often have a knowledge component. For example, a consultant writes up an analysis of a management problem for a client. The value of such outputs is more difficult to measure. Even if client satisfaction (measured via a survey) could be used as a quality measure for the direct deliverables (i.e., the reports), there may be indirect value of the studies. For instance, a consulting job may produce new knowledge that will be valuable to the consulting firm in performing future jobs. These intangible knowledge outputs of white collar work are particularly difficult to value economically until long after the task has been completed.

5. White collar work systems are much more likely to involve self-generated work. Blue collar tasks (e.g., assembling parts, sweeping a floor, ringing up an order on a cash register) generally address requests from the outside. But, because white collar tasks involve a higher degree of creativity, they are not so easily standardized. Hence, it is common for creative and intellectual workers to define at least some of their own workload. Examples include a poet turning an idea into a poem and a consultant adding a task to a consulting job to address an issue that was revealed by previous work.

6. Workers tend to have more discretion over processing times in white collar systems. In blue collar systems, tasks are well-defined and so come with concrete completion criteria. A casting

must be machined to specified tolerances, a room must be cleaned to stipulated standards, etc. But in white collar systems, where work is intellectually complex and/or nonstandard, detailed specifications are difficult to provide. An engineer tasked with solving a design problem has a general idea of what constitutes an acceptable solution. But he/she must use personal judgment to determine when the task is complete; this decision may depend on customer needs, as well as the engineer's backlog of other work. Since the amount of time spent on a task is discretionary, system utilization is not exogenously determined in white collar systems as it is in blue collar systems. Hopp et al. (2007a) showed that this implies important differences in the operating behavior of blue and white collar work systems.

7. Incentives are more critical. As we mentioned earlier, since tasks are intellectual and creative in nature, workers are given more control over task processing. This greater flexibility allows for a large variation in work performance, which suggests that incentives are extremely important in motivating worker behavior. Furthermore, a substantial amount of job satisfaction from white collar work largely is gained through non-pecuniary means, such as peer recognition, task complexity, exposure to smart colleagues, opportunity for self advancement, etc.. Hence, the focus of incentives in white collar work settings should differ from that in blue collar settings. Moreover, due to the difficulty of measuring performance objectively, white collar incentive plans must often be based on subjective measures of performance (e.g., staff evaluations).

By describing the operations of white collar tasks in a manner that highlights the above distinctions from blue collar work, the model in Figure 2 provides a framework for classifying research on white collar work at the individual level. Based on our definition of white collar tasks and the above discussion, some critical aspects of white collar tasks that are distinctive from blue collar tasks are: creativity, discretion, learning, performance measures, incentives, and technology. In the following subsections, we summarize streams of research that have addressed these elements.

3.2 Creativity

Creativity generally refers to the ability to generate novel ideas or solutions that are appropriate to the context (Amabile 1983a, 1996, Amabile et al. 1996, Barron and Harrington 1981). Early studies of creativity revealed the importance of individual characteristics, such as intelligence, broad interests, intuition, self-confidence, attraction to complexity, etc., to creativity (Amabile 1983b, Barron and Harrington 1981, Woodman and Schoenfeldt 1989, Gough 1979). More recent studies have emphasized the impact of task processes and organizational and social environments on creativity. One school of thought has argued that work contexts, such as task complexity, deadlines, goal orientations, perceived evaluations, and supervisory styles affect worker motivation and therefore creative performance (Oldham and Cummings 1996, Shalley 1991, 1995, Shalley et al. 2000, Chesbrough 2003). Work from this stream of research suggests that increasing job complexity and enhancing supportive supervisory style can improve worker creativity (Oldham and Cummings 1996). Another school of researchers have focused on the process of creativity. Fleming and Marx (2006) argued that creativity is a process of combining existing ideas with new ones. For example, research is a creative process implemented by combining existing disparate knowledge streams. MacCrimmon and Wagner (1994) examined creative process through computer simulation. They proposed a creativity model in which the process of creativity can be further divided into "problem structuring, idea generation, and evaluation". A more prevailing view of creativity is to treat creativity as a consequence of social exchange behaviors. Since this view often is examined in the context of organizations, we will extensively discuss it in Section 5.

3.3 Discretion

Another core difference between white and blue collar work lies in discretion, i.e., a worker's power to make decisions regarding processing time, task quality, task sequences, etc. Lack of prescribed detailed operational rules requires workers to handle tasks with high degree of discretion. For example, a consultant may determine how much time to spend writing a report based on his/her judgement of quality; a doctor may determine when to release a patient based on the patient's health condition. These discretionary decisions are important because spending extra time and efforts may add value to the output by either improving the quality (e.g., spending longer time may produce a better consulting report (Hopp et al. 2007a)), increasing the quantity (e.g., a doctor may charge more money for extra service (Debo et al. 2004)), or both. Such discretion is less common in blue collar tasks than in white collar tasks because blue collar work is generally straightforward and well defined. Spending extra time beyond a threshold required to complete the task does not significantly change the output. In contrast, in the more complex setting of white collar tasks, discretion is frequently reflected in task selection, prioritization and scheduling, processing time and output quality. The prevalence of discretion in white collar work makes it difficult to apply many results from blue collar research to white collar work systems because most of research on blue collar work systems is built on the assumption that workers are inflexible or have very limited flexibility (Boudreau et al. 2003, Hopp et al. 2007a).

Because task completion criteria in white collar work settings cannot be specified precisely in most cases, workers must rely on their own judgement to decide when a task in complete since task quality is generally nondecreasing in the amount of time spent on the task, this implies a speed versus quality tradeoff. Workers must somehow negotiate this tradeoff, taking into consideration the effect on future work. Hopp et al. (2007a) modeled this problem using an infinite horizon dynamic program with an objective to maximize value produced per unit time. They showed that optimal processing speed increases (and hence average task quality declines) as the number of customers waiting for service increases. Debo et al. (2004) also made the connection between work load and discretionary task completion in a capacited monopoly service expert situation. They modeled the system as a single-server queue with profit as an increasing function of service time spent, and showed the optimal policy is to increase service speed as work load increases.

While discretionary behavior introduces new problems to OM research, it also provides different insights into well understood problems. A general principle of blue collar work systems is that increasing worker capacity always reduces system congestion (i.e., the number of tasks waiting for labor attention). However, Hopp et al. (2007a) showed through simulation experiments that increasing worker capacity may result in higher system congestion when workers choose to use extra capacity to improve task quality instead of reducing congestion.

3.4 Learning

Learning plays a critical role in white collar work (Argote and Ingram 2000). Because scenarios faced in white collar environments frequently evolve rapidly, workers must continually learn new things to perform well. Learning has been studied extensively in the form of "learning curves" in blue collar settings (Sutton and Barto 1998, Cross 1983, Arthur 1991, Roth and Erev 1995). The core idea behind using learning curves in production systems stems from the observation that workers gain speed and quality through repetitive task processing. Hence, learning is essentially treated as a by-product of doing (i.e., *learning-by-doing*). Learning curve theory is well suited to blue collar work systems because blue collar work is more routine and stable over time than white collar work. In white collar settings, workers rely on ways other than learning-by-doing to gain knowledge because learning in such circumstances is not simply a by-product of doing (Ryu et al. 2005, Carrillo and Gaimon 2004). Existing literature has touched on different aspects of learning, such as exploitation vs. exploration (Toubia 2006), timing decisions (Ryu et al. 2005) and methods of learning (Pisano 1994, 1996).

Because of the complexity of knowledge involved in white collar work, exploitation and exploration are particularly important activities in white collar learning. Exploitation seeks gradual addition of knowledge and leads to a marginal but certain contribution, while exploitation aims to acquire broader and deeper knowledge, and therefore offers a much less certain contribution (Levinthal and March 1993, Toubia 2006). Neither form of learning if without risk. Individuals who are mainly involved in exploitation may fail to achieve needed knowledge, whereas individuals who are exclusively involved in exploration may suffer from obsolescence (Levinthal and March 1993). Hence, maintaining a balance between exploitation and exploration is critical for effective learning. Toubia (2006) studied idea generation with a two-period two-armed bandit model (Bellman 1961) and showed that the choice of strategy (exploitation vs. exploration) is contingent on both the certainty of search and the degree of innovativeness required in the idea.

Ryu et al. (2005) studied the interaction between timing and form of learning. They used a model which maximizes the total net profit of knowledge acquisition within finite time periods, where net profit is the difference between total payoff from knowledge acquired and the cost incurred during the learning process. The value of knowledge acquired is measured as the product of knowledge depth and knowledge breadth. Total cost is measured by the cost incurred in the three distinct learning processes: learning-by-investment, learning-by-doing, and learning-from-others. The optimization decision is how to allocate efforts among these three learning processes. Their results characterize the impact of seven environmental factors (discount rate of cost, discount rate of payoff, salvage value of knowledge, initial knowledge, number of group members, productivity of learning-by-doing, and others' knowledge) on learning decisions and suggest an optimal strategy for the timing and type of learning. Pisano (1994, 1996) examined the forms of learning through empirical studies. The author found that learning-by-doing and learning-before-doing are effective ways of learning in different knowledge environments. "In environments where prior knowledge is weak, high-fidelity feedback requires experiments in the actual production environment ('learning-by-doing'). In contrast, when reliable theoretical models and heuristics exist, laboratory experiments, simulation, and other forms of 'learning-before-doing' can be productively harnessed" (Pisano 1994).

3.5 Performance Measures

A key challenge of studying white collar work system is due to the difficulty of measuring work performance (Davenport and Prusak 2002). In blue collar work, worker utilization, task completion time, output quality and quantity can be objectively measured, while facilitates a number of performance measures for evaluating system performance, including utilization, throughput makespan, failure rate, etc. However, these metrics often do not translate directly to white collar work because the inputs are much harder to measure. For example, using the number of reports a consultant produces within certain period of time (i.e., the throughput) is hardly inappropriate since the quality and complexity of reports may vary greatly. In general since the white collar tasks performed by a single worker often differ significantly (e.g., a lawyer's cases, a doctor's patients and a professor's advisees are all unique), it is difficult to establish uniform metrics of productivity or quality. Finally, white collar work often has a latent impact that can only be measured long after the task is completed. In such cases, fair judgement of output quality upon task completion is almost impossible.

In the literature, there have been a number of efforts to devise simple measures for output evaluation. Gillson et al. (2005) measured latent performance of service technicians by copy machine reliability, which is defined as the average number of copies a machine can make between two customer service calls. Several studies have measured the latent value of academic research publications via delayed recognition in terms of citations (Fleming 2001, Fleming and Marx 2006, Toubia 2006, Almeida and Kogut 1999). Fleming (2001) and Fleming and Marx (2006) used the total number of citations each patent receives by other patents within a certain period of time as a measure of research performance. Toubia (2006) used the number of times an idea is mentioned in later discussions as a proxy for performance of idea generation.

Ramirez and Nembhard (2004) provided an excellent overview of the literature on productivity measurement in knowledge work. They presented a taxonomy, conceptual models, and methodologies addressing 13 dimensions of performance, including "quantity, economic factors, timeliness, autonomy, quality, innovation/creativity, customer satisfaction, project success, efficiency, effectiveness, responsibility/importance of work, KW's (i.e., knowledge worker's) perception of productivity, and absenteeism." This review reveals that, while researchers have made some progress in approximating or measuring white collar productivity, there has been relative little effort devoted to building general system level models based on specific performance measure. Furthermore, as Ramirez and Nembhard (2004) pointed out we still lack methodologies that integrate and cover multiple performance dimensions.

3.6 Incentives

Worker incentives have long been a central issue in operations management. From the piece work systems of the Scientific Management era to the supply chain contracts of the present day, OM researchers have studied the impact of individual motivation on overall system performance. In white collar systems, with their high level of worker autonomy and indirect performance measurement, incentives are particularly important and challenging. More specifically, incentives must motivate learning and creativity, direct discretionary decision making, and enhance adoption and application of new technologies.

Since white collar work is creative and knowledge-intensive, incentives for aligning workers' behaviors with organizational goals should focus on motivating creativity and learning behaviors. Research has shown that means of motivation in white collar work systems go far beyond financial incentives. Previous studies have revealed that task complexity, deadlines, goal orientations, perceived evaluations, and supervisory styles can all be used to monitor worker behaviors (Thompson and Heron 2005, Oldham and Cummings 1996, Shalley 1991, 1995, Shalley et al. 2000, Chesbrough 2003). Researchers have also shown that non-pecuniary rewards, such as receipt of awards, honorary memberships, and peer recognition promotes worker creativity in a significant manner (Eisenberger and Armeli 1997, Laudel 2001). Furthermore, previous research has suggested reward for that creativity in previous task promotes creativity in later tasks and perceived reward for high performance leads to higher perceived self-determination and therefore better performance (Eisenberger and Shanock 2003, Eisenberger and Rhoades 2001, Eisenberger and Armeli 1997).

A critical antecedent to good incentive design is accurate measurement of performance. Although sales revenue is often used to measure the performance of sales managers, such an approximation cannot be readily generalized to many other type of white collar work, especially when the work does not translate directly into financial values and quantity and quality cannot be fairly judged due to the complex nature of the work (e.g., developing a marketing campaign plan). Moreover, the value of many types of white collar work may only be partially measurable upon completion. For example, the value of a new product design may be fully understood only after the product has been on the market for some time. Measurement of such latent value greatly complicates worker performance evaluation. As a result, subjective performance measures (e.g., a manager's rating) are frequently used as bases for incentive plan designs (MacLeod 2003, Ishida 2006). Economists have studied incentive plan based on subjective performance measures in repeated games. MacLeod (2003) showed that when an agent's self-evaluation and the supervisor's evaluation (which are both subjective) are correlated, the optimal compensation is only dependent on the principal's evaluation, although the agent's self-evaluation plays a role in the agent's satisfaction. Subjective measures can also moderate the weakness associated with objective performance measures (Gibbs et al. 2004). In a study of department managers in car dealerships, Gibbs et al. (2004) found that using subjective measures in addition to objective measures positively affect managers' willingness to incur intangible risk, as well as managers' job satisfaction. For more discussion of subjective versus objective measures see Bommer et al. (1995).

Another important aspect of incentives in white collar work settings is motivation in a multi-tasking situation. Workers in white collar work settings often perform multiple or multi-dimensional tasks. In these situations, it is important to use incentives to direct workers to allocate their efforts in a manner consistent with the goals of the organization. Datar et al. (2001) studied incentive plans that allocate worker efforts among multiple tasks using relative weights when neither efforts devoted to each task nor the total effort can be observed. Using a linear contract and negative exponential utility structure Holmstrom and Milgrom (1987) showed how optimal weights can be determined and their relationship to workers' sensitivity to performance measures. Lal and Srinivasan (1993) studied incentive issues of a salesforce engaged in selling multiple products. The authors examined the case where sales effort can be modified multiple times within an accounting period depending on the status of sales realization. Assuming that sales history is known to both the salesperson and the firm, the authors showed that "products with higher sales effort effectiveness, lower marginal costs and lower uncertainty in the selling process should be accompanied by a higher commission rate." Feltham and Xie (1994) considered the case where a worker has multiple inter-correlated goals and imperfect performance measures. Using the multi-task framework introduced in Holmstrom and Milgrom (1991), the authors showed that performance measurement in a multi-tasking setting must consider both the expected value of each task itself and the correlations among the tasks.

Instead of evaluating the impact of incentive on the absolute value of performance, some researchers have studied the incentive problem from a goal-setting perspective (Seijts et al. 2004, Locke and Latham 1990). Presence of goals have been found to positively affect worker performance (Shalley 1991). Shalley (1995) studied the nature of the effect of goal setting on worker productivity and creativity via experiments and concluded that that the presence of creativity goal promotes workers' creativity but impedes their productivity in a complex work setting. Carrillo and Gaimon (2000, 2004) compared the impact of different goals on a manager's decision to invest in knowledge acquisition. They investigated two types of goal settings. The first was a *target goal*, which requires a target to be met and imposes a cost for exceeding or falling short of the target (i.e., two-side goal). They made use of a model in which the cost is expressed as a function of the variance and showed that, when the perceived uncertainty is high, the decision maker will allocate more resources to the behavior that causes less uncertainty. The second type of goal considered by Carrill and Gaimon was a *threshold goal*. The objective is to achieve a result whose expected value is no less than the desired goal (i.e., one-side goal). Their results suggested that when the decision maker perceives high uncertainty with her effort, she is more willing to pursue risky behaviors under a threshold goal scheme than under a target goal scheme. These results yield important insights for incentive goal design associated with knowledge acquisition. For additional literature related to goal setting in work environments, see Berger (1972), Berger (1991), Mantrala et al. (1994), Locke and Latham (1990), Locke and Latham (2004) and Locke and Plummer (2002).

3.7 Technology

Technology is a primary resource in many types of white and blue collar task processing. Often the motivation to use technology is to address tasks for which humans are not intrinsically well-suited. For example, using automated machines to paint cars is a classic use of technology in a blue collar task, while using computers to run a simulation is a prototypical use of technology in a white collar task. The computer revolution has dramatically expanded the range of white collar tasks that can benefit from application of information technology (IT). Moreover, the Internet and various types of knowledge management systems have placed a vast amount of information at the disposal of knowledge workers (Zack and McKenney 1995). This has resulted in increased processing speed, improved average output, enhanced performance, and more consistent quality (Ebel and Ulrich 1987, Dvorak et al. 1997, Carrillo and Gaimon 2004). IT has also played an important role in blue collar work, but in such tasks technology is generally either embedded in the equipment itself (e.g., hardware and software needed to produce a windshield) or used to support established tasks (e.g., computers used to store production data). In either case, the technology stays unchanged throughout the task, that is, no new technology is generated as a result of the task. In contrast, in white collar work, workers interact with technology in a profound manner (Dewett and Jones 2001). Technology improvement (e.g., more advanced analysis tools) or new technology (e.g., a new patent Fleming 2001) is often achieved. Furthermore, information technology is also widely used to support decision making and help generate more creative solutions. MacCrimmon and Wagner (1994) showed that using software to generate alternative managerial policies by making connections among problems and internal and external environments leads to the a greater variety of alternatives and therefore potentially better decision making.

As technology assumes an ever greater role in white collar work, new issues associated with technology management (e.g., technology acquisition and implementation) will continue to emerge (Gaimon

1997, Napoleon and Gaimon 2004). A related challenge is refining our understanding of the value of output in an IT enabled knowledge sharing environment (e.g., the value of contributions to a data base or knowledge management system).

4 White Collar Work at the Team Level

In white collar work settings, tasks often require collective actions by members of teams to achieve designated goals. A team is a social system consisting of two or more people, "which is embedded in an organization (context), whose members perceive themselves as such and are perceived as members by others (identity), and who collaborate on a common task (teamwork) (Hoegl and Proserpio 2004)" A team can also be defined as "(1) a group of employees that is formally established, (2) which is assigned some autonomy (with different intensities and within different organizational areas), and (3) which performs tasks that require interdependence between members (also with different intensities and areas) (Rousseau and Jeppesen 2006)." Representative examples of teams engaged in white collar work are product development teams, consulting teams, administrative teams and information system teams (Janz et al. 1997). Teams can be differentiated from organizations by the degree of task interdependence and the degree of reward interdependence. In an organization, people have shared values in general and receive bonuses that are correlated with the success of the firm. But their actions are not closely integrated and their individual success (e.g., who gets promoted) is not highly correlated. In a group assigned to a set of overlapping tasks (e.g., product development team), members' work is more closely connected as are their rewards. In a team assigned to a very specific task, the work of individuals is so closely connected as to be almost indistinguishable (e.g., a group of consultants produces a jointly written report, an assembly team puts together a piece of machinery). When this is the case, rewards almost have to be highly correlated (e.g., if the consulting report is a success, the entire team benefits). Hence, it is critical for teams to "develop a sense of shared commitment and strive for synergy among members" (Guzzo and Dickson 1996) . For further discussion of important issues related to team management see Kozlowski and Ilgen (2006) and Bettenhausen (1991) for comprehensive reviews.

While team management in production environments has been extensively studied by economists, sociologists, management specialists and OM researchers, much less effort has been devoted explicitly to white collar work systems. Because many white collar tasks are highly collaborative in nature (e.g., engineers designing a product or consultants performing a study), a team focus is very important for white collar work research.

Since teams consist of a collection of individuals, white collar work in teams involves all the issues we discussed at the individual level. In the rest of this section, we focus on the aspects of team work that are central to a framework for understanding white collar work in groups. To provide structure for this framework, we begin by introducing a basic model that captures the major operational elements involved when groups of people work together to carry out white collar tasks.

4.1 A Basic Model

Representing white collar work at the group level requires a model with the same basic elements as the model at the individual level. Workers still receive tasks exogenously and endogenously generate self-work. They still make use of and contribute to the growth of resources. The workers still have finite capacity, which leads to queueing dynamics. But, unlike the model at the individual level, we must now account for interaction between team members and the effect on system performance. Conceptually, team performance is determined jointly by the capabilities and efforts of individuals and the synergy between team members. At a more detailed level, team effectiveness is influenced by interdependence (including task interdependence, goal interdependence, and reward interdependence) among team members, team behavior (collaboration, trust), team learning and incentives.

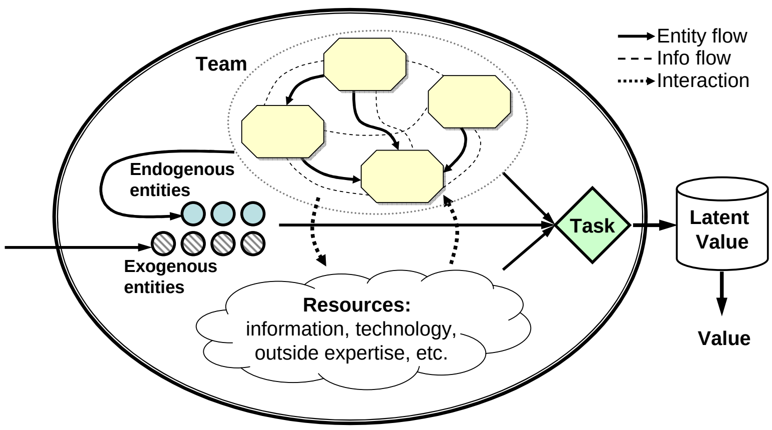

Figure 3: White Collar Work at the Team Level

We depict the basic elements of white collar work at the team level in Figure 3. The main challenge of modeling white collar work at this level is representing the interactions between team members. While teams are common in both blue and white collar work settings, the nature of interaction is different in the two types of work. In blue collar (production) work, teams collaborate on well-defined physical tasks. This raises many interesting questions about how to match individuals efficiently to each other and to tasks over time (see Hopp and Van Oyen (2004) for a discussion and literature survey). White collar collaboration goes beyond these to include knowledge sharing aspects of joint work.[4]. Specifically, in addition to issues related to white collar work at the individual level, at the team level some important issues to consider include:

1. Interdependence is of increasing importance. Intra-team interdependence exists in both blue and white collar work teams but in distinct ways. In blue collar work teams, due to the well-defined physical tasks, interdependence among team members is simple and explicit. In contrast, in white collar work teams, workers face complex and loosely defined tasks. Consequently, they rely on frequent interactions with other team members to gain necessary information and work-related knowledge. For example, engineers in design teams exhibit intense interaction, which has been supported in recent years by the proliferation of CAD/CAM technology (Leonard-Barton et al. 1994). In general, interdependence in white collar work involves much more complex and highly implicit activities (e.g., knowledge sharing (Argote et al. 1990)) than does blue collar work. Consequently, it is critical to understand and manage intra-team interdependence in order to achieve desirable team performance in white collar work environments.

2. Behavioral issues are of paramount importance. The knowledge-based processing involved in white collar work calls for a high degree of team synergy to guarantee collaborations in performing intellectual and creative tasks. Trust, the glue of teamwork, is vital in white collar work and therefore must be incorporated into operations management studies.

3. Learning is critical for effective and efficient team work in knowledge-based processing. Unlike in blue collar work teams, where team members mainly utilize each other's labor, in white collar work settings, team members also rely on each other as repositories of knowledge and information. Therefore, team structure, composition and processes significantly affect knowledge acquisition, dissemination, interpretation and integration in team work.

4. Team incentives need to integrate elements promoting creativity, knowledge sharing, and repeated collaborations. As we noted previously, the intellectual and creative aspect of white

[4]Note that workers we think of as blue collar may also engage in knowledge sharing. For instance, two machinists deciding on the best way to cut a part certainly trade expertise and information. But we would classify such work as a white collar task, since it involves both an intellectual and a creative challenge. This type of situation is why we feel it is important to classify work at the task level, rather than at the occupation level.

collar work increases the difficulty in measuring work performance objectively and forces incentive schemes to rely on subjective measures. The increased dependence on team members for knowledge, information, and creative ideas further reduces the feasibility of financial incentives. Consequently, effective incentive schemes may require sophisticated psychological bases and a range of dimensions.

In the rest of this section, we summarize existing literature related to interdependence, team behavior, learning, and team incentives.

4.2 Interdependence

Intra-team interdependence refers to the extent to which an individual is affected by his/her team members. It plays important roles in predicting team performance (Van der Vegt and Janssen 2003, Janz et al. 1997). For example, team members may foster creativity among each other (Uzzi and Spiro 2005). Interdependence can take various forms, such as task interdependence, goal interdependence, and reward interdependence (Campion et al. 1993). *Task interdependence* refers to the degree to which an individual depends on other team members' skills and efforts to carry out work effectively and efficiently (Van der Vegt and Janssen 2003, Wageman and Baker 1997, Wageman 1995, Campion et al. 1993). It is a combined result of job design and intra-team interactions. *Goal interdependence* refers to the degree to which the achievement of one's goal depends on the goal achievement of other team members (Weldon and Weingart 1993, Campion et al. 1993). *Reward interdependence* refers to the extent to which one's reward depends on other team members' performance (Wageman 1995, Wageman and Baker 1997, Campion et al. 1993).

The research literature has shown that various forms of interdependence affect collaborative behaviors and team performance in different ways. In some cases, they jointly affect performance. For instance, Van der Vegt and Janssen (2003) provided empirical evidence of joint impact of task and goal interdependence. Specifically, they found that, in heterogeneous teams, task interdependence has a strong and positive impact on innovative behaviors when perceived goal interdependence is high, whereas such impact is not found in homogeneous teams. In some other cases, task interdependence has been found to be a significant predictor of collaborative behaviors. For example, Van der Vegt and Van de Vliert (2005) showed in experiments that high skill dissimilarity increases helping behavior in management teams with high task interdependence. Wageman (1995) and Wageman and Baker (1997) studied the interaction between task interdependence and reward interdependence. Wageman

(1995) provided empirical evidence that task interdependence promotes collaboration whereas reward interdependence facilitates monitoring of worker effort. Wageman and Baker (1997) found in an analytical model that while both task interdependence and reward interdependence affect performance, increasing task interdependence rather than reward interdependence leads to increased collaboration. They also suggested that higher task interdependence should be accompanied by higher reward interdependence in order to achieve good team performance.

Researchers have used relatively simple measures to represent interdependence. Van der Vegt and Van de Vliert (2005) measured task interdependence in a lab experiment setting by the percentage of tasks for which one has to exchange information or cooperate with others. The same type of measurement was also used in Cheng (1983). Wageman and Baker (1997) modeled the degree of task interdependence in a two-worker team as a scalar between 0 and 1, with a small number indicating one worker's action has little impact on the other's performance and a large number indicating a huge impact. Each worker's performance was then modeled as the weighted average of his own action and the other worker's cooperative action. In a similar fashion, they represented the degree of reward interdependence by a scalar between 0 and 1. Finally, they modeled a worker's reward as a weighted average of his own performance and team performance, with the degree of reward interdependence being the weight. While these simple representations help model and study the impact of interdependence, our understanding of how to measure interdependence in practice is still very limited. Wageman (1995) provided some examples of measuring interdependence empirically, more comprehensive understanding of this manner is needed.

4.3 Collaboration

Collaboration is the main purpose for all types of teams. A team's collaborative processes may be affected by many behavioral factors, including team members' attitudes, behavior and emotions (Rousseau and Jeppesen 2006), team members' perception about other members' competence (Kim 2003), and team members' proximity over the duration of the task (Hoegl and Proserpio 2004, Hoegl et al. 2007). Rousseau and Jeppesen (2006) reviewed the impact of three categorizes of psychological factors - "attitudes, behavior, and emotions" - on team performance. They concluded that "team characteristics such as interdependence and team autonomy, and psychological variables such as cohesion, commitment, procedural justice, and potency are generally positively associated." In addition to psychological factors, researchers have found that team members' perception of other members' competence has a significant impact on team performance (Kim 2003). The reasoning behind this observation is that perceived high competence of other team members may make one feel his/her own contribution is less important and therefore he/she may devote less efforts. Kim (2003) showed that the impact of perceived competence of team members is significant and contingent on the amount of task information shared. That is, perceived high competence leads to worse team performance when task information is partially shared, but it leads to better performance when task information is fully shared. Finally, the proximity of team members has been shown to have a strong association with team performance. For reviews of team collaboration, see Hoegl and Proserpio (2004) and Hoegl et al. (2007).

4.4 Trust

Collaboration and team performance are often fundamentally dependent on trust, such that an increase in trust can lead to more collaborations and better team performance (Sirdeshmukh et al. 2002, Nooteboom et al. 1997, Urban et al. 2000, Lewicki et al. 1998). This is particularly true in white collar work settings because tasks are highly dependent, work processes and outcomes are highly uncertain, and measurement of task outcomes is ambiguous (Singh and Sirdeshmukh 2000). Since team members cannot observe their mates' performance directly, they have no choice but to trust each other if they are to work together effectively. Because of this, research into the concept of trust, impact of trust on team performance, and modeling of the dynamic nature of trust are relevant to a science of white collar work.

Interpersonal Trust

Interpersonal trust among team members can be defined as "the extent to which a person is confident in, and willing to act on the basis of, the words, actions, and decisions of another" (McAllister 1995, p.25). As such, trust is a multi-dimensional construct that can be classified into *behavior-based trust* and *intention-based trust* (Mayer 1994). Behavior-based trust refers to the willingness to rely on an exchange partner when that party cannot be controlled or monitored. Intention-based trust may further be classified into *competence-based trust* and *benevolence-based trust*. The former refers to the confidence one party has in the other party's capability and reliability (Lieberman 1981), while the latter refers to the confidence one party has in the other party's motives and integrity (Mellinger 1956). Both behavior- and intention-based trust affect team synergy and performance. These constructs of trust have been studied extensively in relational exchange and relational marketing (Morgan and Hunt 1994, Doney and Cannon 1997, Crosby et al. 1990).

Trust is both a predictor and a consequence of interpersonal relationships. Trust is a good predictor of individual behavior and performance. A higher degree of trust leads to greater willingness to engage in risk-taking behaviors (Mayer et al. 1995). Trust also predicts openness, communication, higher level of effort and reduced conflict within teams (Boss 1978, Zand 1972, Dirks 1999, Porter and Lilly 1996). Hence, an appropriate level of trust implies better group performance (Dirks 1999, Friedlander 1970). However, a high level of trust may also result in reluctance to allow mutual monitoring in self-managing teams, and which may hurt team performance when individual autonomy is high (Langfred 2004). In addition to team facilitator of team interaction, trust is also a consequence of teamwork. Empirical study of multi-stage project teams has shown that trust building is dependent on team performance and that high-performing teams are better at developing and maintaining trust (Kanawattanachai and Yoo 2002). The context and speed of trust building are influenced by the reward structure (Ferrin and Dirks 2003), as well as satisfaction and interpersonal factors, such as expertise and timeliness (Crosby et al. 1990, Morrman 1993) and the strength of interpersonal ties (Fleming and Marx 2006). Other issues related to trust have been explored in the literature on relational exchange and relational marketing (Morgan and Hunt 1994, Doney and Cannon 1997).

Operationalizing Trust

From an operations management perspective, it is important to understand how trust can be measured and incorporated into both analytical and behavioral models. There have been some reviews of the existing literature on the measurement of trust (Lewicki et al. 2006, Dietz and Den Hartog 2006). Lewicki et al. (2006) examined the trust development from both behavioral and psychological perspectives (which are organized into four categories based on research approaches, one for behavioral and three for phycological) and answered three major questions in each of the categories: how is trust defined and measured, at what level does trust begin, and what factors affect how trust level changes over time. Dietz and Den Hartog (2006) provides a framework for trust measurement and a content analysis of recent empirical measures of trust.

Although there have been many studies on measuring trust, models that take trust into considerations are very limited. The existing literature that explicitly incorporates trust as a factor in collaborative relationships can roughly be categorized into two schools. One school views trust as unchanged in interactions. For instance, Hwang and Burgers (1997) treated trust as a key component between parties who may benefit from collaborations but are also at risk of being taken advantage of if the other party is noncollaborative. They modeled trust as a probability estimation of cooperation by the other party and assumed it remains unchanged throughout the process of collaborations. This enabled the authors to derive some properties of trust in moderating collaborative decision making. An alternative, and more prevalent view of trust assumes trust to be dynamic and change with interpersonal interactions (Melaye and Demazeau 2005, Castelfranchi et al. 2003, Quercia et al. 2006, Hopp et al. 2007a). This second dynamic school of thought about trust is of particular interest to OM researchers because operations policies, such as flexible work practices and structured teams, may both affect trust levels and be influenced by the nature of trust within the workforce.

Scholars from Computer Science have pioneered the study of trust dynamics. Castelfranchi et al. (2003) used a simulation model to study the interaction between trust and belief. They discussed the role of different belief sources, such as direct experience, categorization, reasoning, and reputation in trust evolution. Melaye and Demazeau (2005) extended the study of belief and trust in a Bayesian framework. The authors examined the impact of direct experience on trust evolution. In their model, trust level is inferred by the truster's basic beliefs, which come from so-called belief sources. Using simulation, the authors showed the impact of positive and negative observations on trust. They also demonstrated that trust may erode in the absence of new experiences. Besides efforts from the computer science field, scholars from operations management have also started to model the impact of trust. Hopp et al. (2007a) incorporated trust into a multi-period supply chain model by modeling trust as a measure of how much a retailer relies on a salesperson's information in demand forecasting. They showed that the retailer's trust in the salesperson leads to improved supply chain person under different various assumptions about the salesperson's motives.

4.5 Learning

White collar tasks often consist of knowledge-based processing, which involves creation, transfer, storage, and utilization of internal and external knowledge. While utilization of internal knowledge is critical, acquisition and application of external knowledge also play important roles in team performance. A team's ability to acquire external knowledge is dependent on properties (e.g., position, tie strength) of the network in which teams are nodes and their work-related communication flows are network ties (Tsai 2001). However, since we will discuss the impact of these properties at the organization level in Section 5, we will focus on team-specific properties (e.g., structural diversity) in the following discussions.

External knowledge generally refers to task-related knowledge, know-how, information, and feedbacks from outside the team boundary (Haas 2006). Knowledge acquisition at the team level is affected by team structural diversity (i.e., how different teams members are with respect to their affiliations, roles and positions (Cummings 2004)). As the diversity increases, team performance due to external knowledge sharing increases because higher structural diversity enables teams to expose to more unique external sources. Schilling et al. (2003) studied the impact of specialization and related work content on learning. Using experiments the authors found that groups working on different but similar tasks over time learn much faster than groups who either are working on specialized tasks or alter between unrelated tasks. Knowledge acquisition is also affected by interruptions, such as "encountering novelty, experiencing failure, reaching a milestone, receiving an intervention, coping with a structural change, redesigning the task, or changing authority" (Zellmer-Bruhn 2003). By examining data on operational teams in three firms in the pharmaceutical and medical products industries, Zellmer-Bruhn (2003) found that interruptions enhance knowledge transferring, which in turn improves the acquisition of new team routines. The impact of external knowledge acquisition is contingent on the conditions of knowledge utilization (Haas 2006). Haas (2006) found that when team conditions are favorable, (e.g., when team members can devote more time to work than the minimum requirement, have more prior work experience, and have more collective control over critical decisions), knowledge acquisition enhances team performance in terms of the quality of projects delivered to clients.

4.6 Incentive

Just as incentive are critical in promoting work efficiency at the individual level, incentive are vital at the team level in white collar work settings. In addition to the issues we discussed in the context of individual motivation, a core issue of incentive at the team level is motivation of collaborative behaviors among team members. Specifically, an incentive plan for teams should address issues of team synergy, integrated creativity and repeated collaborations.

Due to the difficulty of output measurement in most of white collar work settings, incentive plans based on subjective measures have also been studied at team level (Baiman and Rajan 1995, Rajan and Reichelstein 2006). Baiman and Rajan (1995) showed that a discretionary bonus incentive is effective in a two-agent setting. Rajan and Reichelstein (2006) studied a "bonus pool" plan (i.e., the team is informed of how the bonus will be divided based on the realization of noncontractable information). They showed that it is optimal to use a discretionary bonus pool plan when performance can only be measured subjectively. Besides subjective performance measures, another important consideration of team incentives is the impact of repeated interactions among team members. Che and Yoo (2001) studied incentives in a setting of repeated interactions and showed that a joint performance measure (i.e., one in which individual reward is dependent on the performance of others) is desirable because it fosters peer monitoring. Unlike Che and Yoo (2001) who assumed that absolute performance is contractible, Ishida (2006) studied the case when only subjective measures are available and relative team ranking is contractible, and demonstrated the optimality of incentives based on relative performance measures (e.g., awards based on team ranking). This line of research belongs to the literature on relational contracts. For more information please see Baker (1992) and Baker et al. (1994) for related literature.

Besides team incentives based on financial rewards, research has been devoted to understanding nonfinancial incentives. Guimerà et al. (2005) showed a self-assembly mechanism helps teams gain creativity. Others have suggested that the opportunity of being exposed to new collaborators promotes creative team performance (Uzzi and Spiro 2005). Fleming and Marx (2006) also implied that working with new people provides a level of stimulation not found in solitary work. By working with others, people may gain access to new materials or knowledge that is otherwise unavailable to them. As a result, people enhance their creativity by seeking out new collaborations. For a review of empirical evidence related to the performance of team-based incentive see DeMatteo et al. (1998).

It is worth mentioning that traditionally teams have been located in the same geographical place, so that face-to-face interaction comprises the major form of communications among teams members (Zack and McKenney 1995). However, as technology advances, new communication channels, such as phone, email, online discussion space, and tele-conferencing, have made it possible for team members to collaborate at a distance. There is huge literature of virtual teams that studies related issues. Constrained by the length of the paper, we direct interested readers to Zack and McKenney (1995), Hoegl et al. (2007), and Martins et al. (2004) for more information on this issue.

5 White Collar Work at the Organization Level

An organization is a social system in which teams are embedded. As we noted in the previous section, an organization differs from a team in that both the degree of task interdependence and the degree of reward interdependence are relatively low in organizations compared to those in teams. Formally, an organization is made up of multiple individuals and teams. Therefore white collar work in organizations involve all of the issues noted above for individuals and teams, plus some additional ones. Many of these revolve around communication because this is a much more complex activity at the organization level than at the team level. In teams, shared tasks virtually force communication. But in organizations, many different kinds of communication, both formal and informal, occur. Understanding this communication, how it influences performance, and how it is related to organizational structure and management policies is a central concern in white collar workforce management. Moreover, the interactions between information and task processing have dramatically complicated the work system dynamics. We need to study interactions in order to achieve an understanding of white collar work systems and to develop useful models of them.

5.1 The Basic Model

Blue collar production systems are frequently modeled as flow networks by OM researchers (Hopp and Spearman 2000). This provides a mechanism for linking individual process characteristics (e.g., batching, variability, outages, etc.) to system performance metrics (e.g., throughput, cycle time, cost, quality, etc.). Since organizations performing white collar work also consist of individual processes (i.e., people) who coordinate to complete tasks, it is appealing to view them as flow networks as well.

Unfortunately, a straightforward translation of the production flow network models to white collar work settings is not appropriate due to the differences between blue and white collar tasks we have discussed earlier. Nonroutine intellectual work poses individuals with situations where they must seek out and acquire useful knowledge dispersed among subunits in the organization (Hansen et al. 1999). Hence, in addition to the work flow, which is formal and direct, there is information flowing among different subunits, which is often informal and complex (Huberman and Hogg 1995).

As shown in Figure 4, an organization contains multiple subunits performing white collar work. Each subunit contains a team of one or more workers. Subunits can perform their own tasks, as well as collaborate with other units on more complex tasks. When teams participate in complex task processing, they are linked by either deterministic or probabilistic job flows. These systems can therefore be represented by stochastic networks similar to those used in blue collar work modeling (Adler et al. 1995). When teams perform independent work in parallel, they can be treated as a single team. They can either solve the problem at hand or seek support from other subunits (e.g., searching and acquiring knowledge) or pass it onto to another team that is perceived to have the potential to solve the focal problem.

As shown in Figure 4, from a modeling perspective, a white collar work system can be viewed as a superimposed network in which informal networks of information flow are combined with task processing networks. While this conceptual model only lays out the basic dynamics of white collar

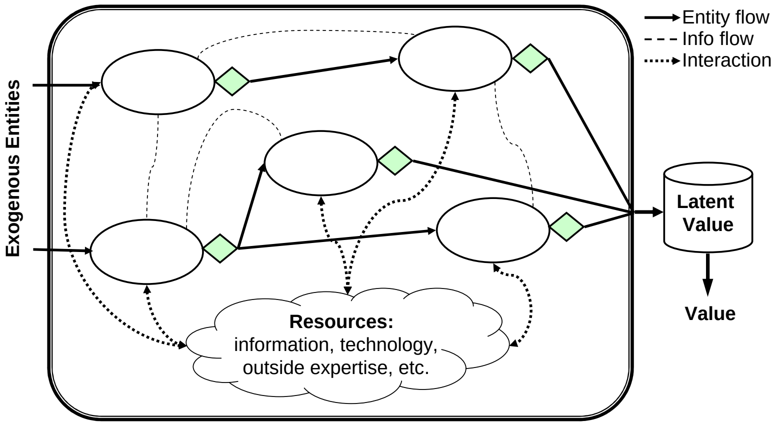

Figure 4: White Collar Work at the Organizational Level

work systems, it highlights many important issues in studying white collar work at the organization level.

1. The organizational structures need to address issues created by knowledge-based processing. Since the intellectual and creative content of tasks makes task coordination in white collar work settings fundamentally different from that in blue collar systems, proven methods from blue collar settings, which rely on standard operating procedures and do not take knowledge and information as inputs, cannot be applied directly to white collar work systems. Consequently, we need new coordination systems which integrate the knowledge and information elements into the task processing framework.

2. New and more flexible control systems are needed. In blue collar work systems, process control relies largely on standardization and rigid structures (e.g., the serial production line). However, those control systems are generally ill-suited to control white collar work systems because the intellectual and creative content of white collar tasks calls for discretion and flexibility. Hence white collar work requires methods that recognize and enhance the creative and intellectual components of white collar work.

3. Organizational learning, which involved knowledge seeking and sharing, has become an increasingly important mechanism by which firms can sustain a competitive advantage. Since knowledge-based task processing is highly dependent on knowledge and information input (Grant 1996), individuals and teams frequently rely on information and expertise located elsewhere in the organizations to perform tasks. A great deal of performance variation is due to a lack of information and not being able to access external expertise in a timely fashion. While an or-

ganization may formally design its coordination system and create an infrastructure to support organizational learning, knowledge seeking and sharing largely occur through interactions which are not defined by formal organizational structures. Hence, a science of white collar work requires an understanding of knowledge seeking and sharing via informal channels.

In the rest of this section, we review previous research related to the critical issues of structure, control systems, and learning.

5.2 Structure

Knowledge-based task processing is embedded in established organizational structures and communication patterns (Sosa et al. 2003). The most widely studied organizational structures in white collar work environments are hierarchical, modular, and network structures.

5.2.1 Hierarchical Structures

Classical centralized coordination is characterized by the hierarchical organization structures, which has a pyramidal form. Many white collar work systems are coordinated with such structures. For example, risk management in investment banking is hierarchical, in which each unit of the firm determines its portfolio of risk activities and the overall level of risk is controlled by the risk managers (Vayanos 2003).

Garicano (2000) and Garicano and Rossi-Hansberg (2006) studied the optimal organizational structure in the situation where heterogeneous agents face heterogeneous tasks. Heterogeneity among agents is defined according to their different level of knowledge. An agent can handle a task only when her knowledge level exceeds that required for task processing. If an agent fails to solve a task, he/she may choose to acquire knowledge at some cost or to search for help from other agents with a communication cost represented by the reduced production time. Garicano (2000) showed that the optimal structure for such organizations is a knowledge hierarchy, in which the knowledge of each level is non-overlapping and the size of each level decreases as the knowledge level increases. Garicano and Rossi-Hansberg (2006) extended Garicano's findings to characterize the organizational structure by *positive sorting* (i.e., "higher ability agents share their knowledge with higher ability subordinates") and *skill stratification* (i.e., "individuals are segmented by cognitive skills").

Motivated by portfolio formation in investment banks, Vayanos (2003) studied a hierarchical procedure of information processing when communication must occur along hierarchical lines and local information processing by workers is pervasive. Assuming aggregation incurs information loss, Vayanos showed that in the optimal organizational structure all workers have only one subordinate and all workers but one work at their full capacity.

While these studies provide us valuable insights into organizing knowledge-based processing hierarchies, they are limited in two aspects. First, they have ignored the interaction among workers at the same level in performing tasks. Second, and more importantly, they do not account for the fact that smart people often ignore hierarchy because they know that centralized management stifles thinking and hinders diversity of ideas (Goffee and Jones 2007).

5.2.2 Modular Structures

A modular organization is a loosely coupled system consisting of elements that independently perform distinct functions (Sanchez and Mahoney 1996, Pil and Cohen 2006) and is an effective means of organizing complex and flexible work systems (Baldwin and Clark 2000). Research has found that modularity enhances a firm's capability by allowing greater processing flexibility, which improves its fitness in a dynamic environment (Pil and Cohen 2006). For example, firms may provide a larger variety of product or services through recombinations (Thomke and Reinertsen 1998). Modularity also promotes a firm's sustained competitive advantage by enabling it to adapt more quickly and act on opportunities more effectively (Pil and Cohen 2006). Because of these advantages, white collar work is often organized in modules. Product development teams are a prototypical example of such structure. But since modules can be formed and combined in many ways, this leaves the question of what is the best module structure for a given organization. Moreover, performing tasks assigned to modules often require interactions beyond the boundaries of individual modules. Because of this, a common problem found in modular organization is that they can limit the interdependence among modules and thereby hinder innovation (Fleming and Sorenson 2001). For an extensive discussion on modularity, see Sanchez and Mahoney (1996).

5.2.3 Network Structure

In white collar work systems "the critical input in production and primary source of value is knowledge" (Grant 1996). Production requires coordination from individuals and teams possessing different expertise (Grant 1996, Dewatripont and Tirole 2005). Formal hierarchies and modular structures often fail to promote the timely communication and effective collaborations required for good performance. As a result, informal networks (where workers are represented by nodes and relations among workers are depicted by ties (see e.g., Cross and Borgatti 2006, Burt 2004, Cummings 2004) have been found embedded in many organizations.

One form of network that has been found to match the communication/relation network in many white collar settings is the *small-work network* (Watts and Strogatz 1998). For example, this structure has been observed among actors and scientists (Uzzi and Dunlap 2005). Small-world networks are characterized by high clustering (i.e., the probability a friend's friend is a friend) and small diameter (i.e., the average minimum number of steps between any two nodes) (Watts and Strogatz 1998, Watts 2004, Uzzi and Spiro 2005). Clustering reflects local density and diameter reflects separation (Uzzi and Spiro 2005). The short average path length implies that information may flow quickly between different clusters and therefore enhance creativity by allowing combination of disparate knowledge. Meanwhile, high clustering allows local sharing and collaboration. See Watts (2004) for an review of the charactersitics and applications of small world networks.

Huberman and Hogg (1995) took a different approach to study network organizations. Instead of matching task types with expertise, the authors focused on hint (an idea that has potential value to the receiver) sharing and helping behaviors among workers using an analytical model. In their model each worker, who performs a multi-step task, chooses either to work by herself or use a hint sent by others at each step. The value of a hint is dependent on both the content of the hint and how fresh it is to the receiver. Nasrallah and Levitt (2001) used a similar framework of hint sharing to examine how timely access affects the probability of successful interaction. These studies are particularly relevant to the operations management field because their use of a flow representation makes them analogous to the flow models prevalent in production and supply chain research.

Since networks are an important form of organizing white collar work, it is very useful to understand how networks form and evolve in various conditions. A intuitive assumption of network formation is decentralized decision making on the part of the workers. Economists have developed models in network formation under this assumption. For example, Bala and Goyal (2000a) studied network formation using a non-cooperative model, in which any individual may initiate a new link with others with by paying some cost. Their results showed that the network converges to an equilibrium social network with simple structures. When formation of a link provides benefits to only one party (e.g., one individual provides expertise to another), the network in Nash equilibrium is either empty or a wheel. When formation of a link benefits both parties (e.g., two individuals collaborate), the final network can be either empty or a star. Many other researchers have formulated network formation models based on probabilistic attachment rules and game theoretic behavior (see Wolinsky (1993), Slikker and van den Nouweland (2001), Jackson (2003), and Watts (2004) for examples and information).

5.3 Control Systems

Control systems are mechanisms that clearly specify the appropriate methods, behaviors, and outcomes of the system (Turner and Makhija 2006). They generally take one of two forms: process-based control and outcome-based control. Process control, often based on work standardization, is widely used in blue collar work systems to achieve superior performance. In white collar work settings, although tasks are nonroutine in nature, appropriately designed process control can still be applied to gain good performance (Nidumolu and Subramani 2003, Turner and Makhija 2006).

Since white collar work is knowledge-based, the tradeoff between standardization and discretion processing is of particular importance in designing control systems for white collar work settings. Standardization refers to uniform definition of processing methods and/or performance criteria, while discretion involves the flexibility in making decisions or being evaluated based on different standards (Nidumolu and Subramani 2003). Nidumolu and Subramani (2003) examined the role of standardization and decentralization in controlling both white collar work process and performance. when they are applied to different targets, (e.g., to task processing or to outcome measurement). By studying software development firms, the authors found that a combination of standardization in performance measures across projects and decentralization in work process decision making enhances performance.

The effectiveness of process control in white collar settings also depends on the features of the knowledge (e.g., codifiability, completeness, diversity) being controlled (Turner and Makhija 2006). Codifiability refers to the fact that knowledge can be broken down into small and easily understood pieces. When knowledge is highly codifiable, it is relatively easy to break the process and therefore is possible to implement more standardizations in the process control. Completeness refers to the degree to which knowledge necessary for task processing is available to the worker. When knowledge is complete, which indicates less uncertainty involved in task processing, a more standardized approach is recommended. Diversity refers to the breadth and relatedness of knowledge. When knowledge is less diversified, more standardization may be applied to process control.

As we discussed previously, information serves as critical input to white collar task processing. Knowledge of information location, direction, and its integration with entity flows is necessary for designing effective control systems. Unlike in blue collar work system where information flow is sequential (i.e., it flows in a predetermined sequence), information flow in white collar work systems can be sequential or reciprocal (i.e., it flows back and forth and follows no predetermined sequence)

(Egelhoff 1991). Huberman and Hogg (1995) provided an example of integrating information into task processing by modeling hints as "raw materials" for knowledge-based processing.

5.4 Learning

Learning in the forms of knowledge seeking and sharing comprise a critical aspect of organization competence. Since white collar workers often encounter work problems that can only be solved with support from others in the organization in terms of information, knowledge or help, the ability to learn (i.e., seek information and share knowledge) is almost always vital to white collar work performance. For example, Burt (2004) showed that a supply chain manager may be able to produce more good ideas if she shares information and knowledge with other supply chain managers. Huston and Sakkab (2006) found that R&D workers at Proctor&Gamble are able to greatly improve their performance by actively sharing information. The knowledge seeking and sharing behaviors are represented in the basic model of Figure 4 as an informal network of informational flow superimposed on a formal task processing network. The entities that flow through the informal network are work-related knowledge and information whose presence may facilitate task processing. Although knowledge seeking and sharing behaviors have become critical to worker performance, there has been little work in the OM community examining such behaviors. Hence, we treat seeking and sharing as two distinct procedures and discuss the impact of various factors on these procedures.

Before we discuss knowledge seeking and sharing, it is necessary to understand different types of knowledge. Based on the difficulty of being codified (Argote and Ingram 2000), knowledge can be classified into two types: tacit and explicit. *Tacit* knowledge refers to knowledge that is hard or even impossible to codify and therefore is difficult to share through systematic means (Nonaka 1994, Zander and Kogut 1995). In contrast, *explicit* knowledge is codifiable and can be easily transferred via "formal and systematic language" (Nonaka 1994, Zander and Kogut 1995).

5.4.1 Knowledge Seeking

Information or knowledge seeking refers to the activities of locating useful information or knowledge sources (Hansen 1999, Morten et al. 2005). The decision and efficiency of knowledge seeking within the organization is affected by the informal networks embedded in formal organizational structures, the network within the team, and the competition within the organization. Examples of such networks are the *awareness network* (in which a directional tie represents the former has specific knowledge about the latter), *information network* (in which a directional tie represents the former seeks helps from the latter), and *collaboration network* (in which a non-directional tie represents joint work) (Cross and Cummings 2004). The most important properties of networks associated with knowledge seeking are network structure (i.e., node position, number of ties, etc.) and tie strength (i.e., the frequency and intensity of interaction). Larger numbers of direct connections implies a higher likelihood of locating the right knowledge source and higher absorptive capacity (i.e., the common knowledge base necessary for absorbing new knowledge) due to past interactions (Hansen et al. 2005) and therefore incurs a lower search cost. However, most research has found node position, rather than the number of direct ties, to be a more significant predictor of searching efficiency. Individuals who occupy positions characterized as "structural holes" or "brokerage positions" are more likely to be exposed to new information and thereby gain timely access to new knowledge more quickly and more frequently (Burt 1992, 2004, Tsai 2001). Besides network structure, tie strength is another important factor affecting search efficiency. Weak ties, referring to distant and less frequent relationships, are efficient for knowledge seeking because "they provide access to novel information by bridging otherwise disconnected groups and individuals in an organization" (Hansen 1999). In contrast, strong ties may impede seeking out new information because people who share strong ties tend to have common friends or tend to have largely overlapped knowledge pools (Granovetter 1978, Reagans and McEvily 2003). Hansen et al. (2005) showed that higher network intensity (i.e., the number of established ties divided by the total number of possible ties) within new product development teams leads to less knowledge seeking from outside the teams. They also showed that greater competition among teams leads to higher sharing cost measured by time spent in communicating and gathering new knowledge.

In addition to understanding knowledge seeking behaviors through empirical or behavioral studies, researchers have also modeled knowledge seeking using analytical models, some of which make use of methodologies used to model blue collar work system (e.g., queueing theory). These models provide useful insights into issues, such as task and expertise matching, helping and idea utilization, and efficiency of interaction. For instance, Guimerà et al. (2002b) modeled an organization where heterogeneous tasks and expertise are initially mismatched and tasks need to be delivered to workers with matching expertise. This process is completed via searching and transferring. In their model, the cost of search is proportional to the average distance a task travels before it reaches its destination. In a queueing framework, assuming a task may travel through all possible paths, the authors showed that the congestion (i.e., total task arrival rate) at each node is proportional to the betweenness of the worker (i.e., total number of possible paths a worker occupies) in the informal networks. Guimerà et al. (2002a) considered the same type of organization and incorporated quality of channel into the original model. They modeled the quality of the network tie as the geometric average of the capability (a decreasing function of number of tasks currently at the worker) of the sender and receiver, with higher channel quality indicating faster speed. Their results also characterized the relation between network congestion and network structure.

5.4.2 Knowledge Sharing

Knowledge sharing is affected by many factors: the properties of knowledge (i.e., tacitness) (Hansen et al. 1999), the strength of the ties through which knowledge is transferred (Granovetter 1978), absorptive capacity of the recipients (i.e., "prior related knowledge and diversity of backgrounds")(Cohen and Levinthal 1990), and mobility of the worker (Jaffe et al. 1993, Almeida and Kogut 1999). Knowledge sharing is affected by the type of knowledge being transferred. The tacitness of knowledge determines the channel through which knowledge is sought and accumulated. When knowledge is largely tacit, workers rely on complex interactions. For example, Hansen et al. (1999) found that in organizations which provide standard services or product knowledge is mainly shared in codified form, such as person-to-person interaction. Strong personal ties have been found useful in interpreting and absorbing tacit knowledge. This is because strong ties (i.e., ties maintained through frequent and intensive interactions (Granovetter 1978, Hansen et al. 2005)) promote mutual trust and understanding and therefore facilitate complex knowledge sharing (Krackhardt 1992, Burt 1992, 2004, Granovetter 1978, 1985, Hansen 1999, Fleming and Marx 2006, Cross and Borgatti 2006, Borgatti and Foster 2003). Moreover, the recipient's relevant knowledge, experiences, and diversity of backgrounds also improves sharing effectiveness (Cohen and Levinthal 1990, Szulanski 1996).

Almeida and Kogut (1999) studied the impact of a worker's mobility on knowledge sharing. The authors showed that the mobility path of patent holders leads to inter-firm knowledge spillover. (For a more detailed review of the impact of mobility and research methods using networks see Brass et al. (2004), Brown and Duguid (2001), Tsai (2001), Ibarra and Andrew (1993) and Marsden (1990).) Moreover, information redundancy and timely access to information sources affect knowledge sharing efficiency (Huberman and Hogg 1995, Nasrallah et al. 2003).

While knowledge sharing is essential to white collar work, it can become a barrier to performance if not motivated appropriately (Lee and Ahn 2005). One reason is that knowledge sharing is costly. For example, in some cases, people may worry that their work process will be interrupted and therefore may be reluctant to help others when approached for information. In other cases, people may release partial or false information for fear of being outperformed by their peers. Hence, promoting honest and efficient sharing is of great importance to organizations. In the business world, Bain and Company has incorporated how much help a person provides to others into his/her annal compensation (Lee and Ahn 2005). Unfortunately, research in this area is very sparse and our understanding is still very limited.

In Table 1, we summarize the literature. We have reviewed above as relevant to white collar work at the individual, team and organizational levels. In addition to organizing the many streams of research by level and topic, this table further breaks them down according to research methodology (i.e., analytic, empirical or behavioral/empirical). By providing a high level summary of the coverage in the literature of the key issues involved in understanding the operations of white collar work, this table provides a platform for identify promising directions of future research.

Table 1a. White Collar Work at Individual Level

	Analytical	Empirical	Behavioral/Experiments
Creativity		Amabile et al. (1996) Shalley et al. (2000)	Barron and Harrington (1981) Amabile (1983a) Woodman and Schoenfeldt (1989) Shalley (1991) MacCrimmon and Wagner (1994)[s] Shalley (1995) Oldham and Cummings (1996) Shalley and Gilson (2004)
Discretion	Debo et al. (2004) Hopp et al. (2007a)		
Learning	Toubia (2006)	Levinthal and March (1993) Pisano (1994) Pisano (1996)	Ryu et al. (2005)[s]
Performance measure	Ramirez and Nembhard (2004)[r]	Fleming (2001) Gillson et al. (2005) Fleming and Marx (2006)	Toubia (2006)
Incentives			
Motivation		Oldham and Cummings (1996) Laudel (2001) Chesbrough (2003) Thompson and Heron (2005) Davenport et al. (2007)	Locke and Latham (2004) Gottschalg and Zollo (2007)
Subjective Measurement	Feltham and Xie (1994) MacLeod (2003) Ishida (2006)	Gibbs et al. (2004)	Bommer et al. (1995)
Multi-Tasking	Holmstrom and Milgrom (1991) Lal and Srinivasan (1993) Feltham and Xie (1994)[r] Datar et al. (2001)		
Goal-Setting	Carrillo and Gaimon (2004)	Seijts et al. (2004)	Shalley (1991) Shalley (1995) Locke and Plummer (2002)
Technology	Napoleon and Gaimon (2004) Carrillo and Gaimon (2004)	Zack and McKenney (1995)	Dewett and Jones (2001)

s: simulation; r: review

Table 1b. White Collar Work at Team Level

	Analytical	Empirical	Behavioral/Experiments
Interdependence	Wageman and Baker (1997)	Leonard-Barton et al. (1994) Van der Vegt and Janssen (2003) Uzzi and Spiro (2005)	Weldon and Weingart (1993) Campion et al. (1993) Wageman (1995) Van der Vegt and Van de Vliert (2005)
Collaboration		(Kim 2003) (Hoegl and Proserpio 2004) (Hoegl et al. 2007)	(Rousseau and Jeppesen 2006)^r
Trust	Hwang and Burgers (1997) Melaye and Demazeau (2005) Quercia et al. (2006) Hopp et al. (2007b)	Morgan (1995) McAllister (1995) Porter and Lilly (1996) Doney and Cannon (1997) Dirks (1999) Kanawattanachai and Yoo (2002) Ferrin and Dirks (2003) Langfred (2004)	Crosby et al. (1990) Lewicki et al. (1998) Lewicki et al. (2006)^r
Learning		Tsai (2001) Hansen (2002) Zellmer-Bruhn (2003) Cummings (2004) Haas (2006)	Schilling et al. (2003)
Incentives	Baiman and Rajan (1995) Che and Yoo (2001) Rajan and Reichelstein (2006) Ishida (2006)	DeMatteo et al. (1998)^r Fleming and Marx (2006)	Cameron and Pierce (1994)^r Guimerà et al. (2005)^s

s: simulation; r: review

Table 1c. White Collar Work at Organization Level

	Analytical	Empirical	Behavioral/Experiments
Structure			
Hierarchical	Radner (1993)		Dupouet and Yildizoglu (2006)^s
	Garicano (2000)		
	Vayanos (2003)		
	Garicano and Rossi-Hansberg (2006)		
Modular		Fleming (2001)	Sanchez and Mahoney (1996)
		Pil and Cohen (2006)	Baldwin and Clark (2000)
Network	Bala and Goyal (2000a)	Uzzi and Spiro (2005)	Watts and Strogatz (1998)^s
	Dupouet and Yildizoglu (2006)		Slikker and van den Nouweland (2001)
			Watts (2004)^r
Process Control	Huberman and Hogg (1995)	Egelhoff (1991)	Turner and Makhija (2006)
		Nidumolu and Subramani (2003)	
Learning			
Knowledge Seeking	Guimerà et al. (2002b)	Hansen (1999)	Granovetter (1973)
		Hansen (2002)	Granovetter (1983)
		Reagans and McEvily (2003)	Cross and Borgatti (2006)
		Burt (2004)	
		Cross and Cummings (2004)	
		Hansen et al. (2005)	
		Morten et al. (2005)	
Knowledge Sharing	Huberman and Hogg (1995)	Ibarra and Andrew (1993)	Argote et al. (1990)
	Nasrallah et al. (2003)	Zander and Kogut (1995)	Cohen and Levinthal (1990)
		Szulanski (1996)	Burt (1992)
		Hansen et al. (1999)	Krackhardt (1992)
		Almeida and Kogut (1999)	Nonaka (1994)
		Tsai (2001)	Brown and Duguid (2001)
		Brass et al. (2004)	Borgatti and Cross (2003)^r
		Fleming and Marx (2006)	

s: simulation; r: review

6 Research Opportunities

The above survey shows that considerable research has been done on issues related to white collar work. But when held against the standard of a coherent science of white collar work, this literature is still fragmented and only loosely connected to operations management. Furthermore, the various research methodologies have been applied unevenly to important problem areas. For example, knowledge transfer has been studied extensively with empirical methods but analytic models of knowledge transfer processes have been rare. As a result, we have not yet incorporated many important insights from the literature into OM models of white collar work.

In this section, we use the survey as summarized in Table 1 to highlight some major gaps and suggest research directions that are fundamental to building a science of white collar work operations.

6.1 Performance Measurement

Operations Management is a prescriptive field. The ultimate goal of all OM research is to improve the design and management of operations systems. Hence, an essential element of the science of operations for any class of systems is an accurate characterization of performance. This is certainly true for white collar work systems. Each of the base models presented above include some form of output process, which could be characterized in terms of value, knowledge, customers satisfaction, or other ways depending on the specific environment. To use these models as a framework for developing a operational science of white collar work, we need concrete performance metrics that can be connected to policies.

Unfortunately, accurate measurement of white collar work output is extremely difficult. "Most traditional HR metrics - such as employee turnover rate, average time to fill open positions, and total hours of training provided cannot accurately predict organizational performance" (Bass and McMurrer 2007). Davenport (2005) suggested that the best way to circumvent this problem is to "Hire smart people and leave them alone". While this might work in some settings, it is hardly a basis for a science of white collar work.

To develop rigorous performance measures for white collar work systems, we probably need to look to previous research on blue collar work systems for inspiration. A number of standard performance measures, including throughput, WIP level, utilization, customer satisfaction, etc., are commonly used to characterize blue collar work systems. While some of these may translate directly to white collar settings, many do not. For example, since workers have discretion over the amount of time they spend on a particular task (Hopp et al. 2007a), utilization is a difficult concept to apply in white collar settings. Indeed, it is quite possible that all white collar workers in a system are 100 percent utilized (e.g., a statistician may seem to work all the time: crunching data in a computer, discussing models with peers, etc.). Consequently, the key issue is not how busy workers are, but rather how they allocate their time. New metrics are needed to measure the efficiency and effectiveness with which white collar workers do this.

Another issue that complicates performance measurement of white collar work is the latent value of such work. For example, a decision by a manager may have consequences that extend well beyond his/her time as a manager (Feltham and Xie 1994). Since many white collar tasks are knowledge based, white collar work often makes contributions to the knowlege base of the organization, which are difficult to evaluate in the immediate term. However, while latent value is an important feature of white collar work, we have only seen it examined in empirical studies. There has been almost no effort to model latent value analytically in operations management studies. Consequently, we do not yet have means for incorporating latent value of white collar work into analyses of OM-related policies, such as incentive plans, prioritization schemes and collaboration mechanisms.

Even measures that do translate from blue to white collar settings may require modification to be useful in white collar systems. For example, customer satisfaction (Lapre and Tsikriktsis 2006) is appropriate in both blue and white collar settings where customer satisfaction can be measured. In blue collar settings where repetitive products and/or services are provided to customers, simple survey methods can yield reasonable measures of satisfaction. For example, Fornell (2005) measured customer satisfaction at the firm and industry level. But, because important outputs of white collar work (e.g., contributions to organizational knowledge) are not immediately experienced by customers, many white collar work systems cannot be reasonably evaluated in customer satisfaction terms. Nevertheless, when a white collar task is closely connected to a product and/or service, customer satisfaction metrics are key measures of performance. For example, Eisenberger et al. (2007) used customer satisfaction to predict the performance of movie scripts. Straub et al. (1995) studied the role of information technology in measuring system usage and integration of objective (i.e., computer-recorded) with subjective (i.e., self-reported) system measures. Research on the collection, analysis and connection of such metrics to operating policies is essential to the development of a science of white collar work.

6.2 Integrated Work and Information Networks

The OM field has developed a rich literature using network flow models to represent the dynamics of blue collar work systems (e.g., Hopp and Spearman 2000, Buzacott and Shanthikumar 1993). The flows in such models are physical entities, such as parts, jobs or customers. Such models have also been applied to some white collar work system. For example, Adler et al. (1995) applied the idea of network flow models in a module-based project development management. Their findings suggest that some of the basic principles of blue collar work (e.g., impact of bottlenecks, variability and flexibility) are applicable to white collar work that can be represented as network flows. However, research in this area is till sparse and we do not yet have a good understanding of how broadly these principles apply.

However, in knowledge intensive white collar work systems, information flows are at least as important as physical flows. Research has shown that information sharing is strongly related to ties among workers, which can range from informal to official (Uzzi 1996, Uzzi and Lancaster 2003). Hence, methodologies developed in social network analysis offer strong potential for application to OM modeling of systems wehre information and task processing are embedded in work-related social relationships. Analytic and empirical research into models that integrate social networks into task flow models offers a promising avenue for creating a formal platform for representing white collar work systems.

A network representation of white collar work systems raises the issue of how the network is coordinated. In blue work systems, coordination is generally achieved via work process design (e.g., work is organized into a serial production line). In white collar work settings, as information is an important input to knowledge-based processing Grant (1996). For example, a doctor facing a unfamiliar symptom may require advice from more experienced doctors before deciding on a course of treatment. Because the work is less structured than in blue collar systems, it is not usually practical to impose a rigid structure on the work flow. Hence, white collar systems must rely on a mixture of centralized control (e.g., a manager makes task assignments and coordinates dynamic adjustments) and decentralized evolution (e.g., workers direct their own search and collaboration activities). Analytic, empirical and behavioral research into coordination mechanisms is therefore vital to a science of white collar work operations. Of course, to carry out this research we need the previously discussed performance metrics to represent effectiveness.

Finally, the effectiveness of white collar work networks is strongly influenced by the flexibility of the constituent workers. It is well known that flexibility is of fundamental importance in blue collar work system analysis (Sethi and Sethi 1990, Gerwin 1993). Cross-training is an effective way to improve system flexibility because cross-trained workers represent capacity that can be shifted to where it is needed most. As such, flexibility can result in increased throughput, reduced work-in-process or improved customer service. In white collar work systems, most workers perform work in a multi-tasking fashion. For example, a consultant communicates with clients, identifies problems, develops strategies, and helps client implement management policies to achieve desirable results. A professor teaches, performs research, and advises students. Obviously, flexibility is a prerequisite for such multi-tasking behavior. From a research standpoint, much remains to do to raise our understanding of the role of flexibility in multi-tasking, white collar environments to that we have attained for flow-oriented blue collar systems.

6.3 Bottleneck Analysis

One of the major insights that has come out of network flow analysis of blue collar work systems is the importance of bottlenecks. Because bottlenecks constrain system capacity, they are fundamental in determining throughput, cycle time, customer service and other performance metrics. Similar dynamics apply to some white collar systems. For example, in a multi-step software development project, productivity is constrained by the least productive steps regarding both processing speed and output quality. However, bottleneck analyses are seldom used in white collar systems. The reason is that the standard definition of a bottleneck (i.e., the station with the highest utilization (Hopp and Spearman 2000)) may be inappropriate in white collar work systems: (a) a white collar worker's time is generally fully utilized, and (b) the quality of white collar tasks can vary greatly, which means that measuring the quantity of tasks completed does not fully capture worker output. Moreover, the knowledge-intensive and non-repetitive nature of white collar tasks also dramatically complicates bottleneck analysis. Hence, basic modeling research is needed to develop a white collar analog to traditional blue collar bottleneck analysis.

6.4 Discretionary Decision Making

A key characteristic of white collar work systems that distinguishes them from blue collar systems and complicates modeling and analysis is the high degree of discretion in decision making. Task selection, prioritizing, completion, and self-generated work all require discretionary choices on the part of workers. For example, when helping a customer select a car, a salesperson has the freedom to choose which options to recommend and how to price them (within limits). Similarly, the salesperson may choose to speed up processing of current customer if other customers are waiting. Such discretion makes it difficult to predict the behavior of both individual workers and the overall system. Although there has been limited work to model these systems by using a dynamic optimization framework (Hopp et al. 2007a), our understanding of how these systems actually operate in practice is still very limited. To improve the management of discretionary decision making, we need to: (*i*) identify the areas where discretionary decision making is critical (e.g., task prioritization, time allocation, multi-tasking, information search, etc.) (*ii*) identify the main factors (e.g., tight deadlines, reward structures, nature of tasks) that impact discretionary decision making, (*iii*) develop normative models of optimal discretionary decision making in white collar work settings, and (*iv*) perform empirical studies of white collar workers in various environments to determine how they actually make decisions concerning the discretionary aspects of their work and compare these to optimal strategies.

6.5 Trust

Trust has always been an important element of the business world. But it is becoming even more vital in the workplace as a result of increased diversity of the workforce, participative management styles and implementation of work teams (Mayer et al. 1995). Trust plays a critical role in many aspects of white collar work settings. For example, research has shown that trust affects information sharing (Hopp et al. 2007b, Terwiesch et al. 2004), worker effort and mutual monitoring in self-directed teams (Langfred 2004), supply chain decisions (Taylor and Plambeck 2007), and project management activities (Sommer and Loch 2003). However, while trust is of paramount importance to the execution of white collar work, efforts to incorporate it into OM research have been limited. In contrast, as indicated by our literature review, research in other fields, such as general management, sociology, and computer science, have provided us with a great deal of insights into factors leading to trust, trust itself, and outcomes of trust. Hence, we believe that OM scholars may find these results of value when trying to account for the impact of trust on human behavior in operations settings. Examples include the influence of trust between a manager and a consultants on incentive plan design, the effects of trust levels among teams members on their decisions of whether and where to seek and/or provide help, the role of trust in influencing collaborative behavior in repeated settings. These and many other situations of importance to a science of white collar work can only be understood if trust can be modeled and incorporated into operations models.

6.6 Learning

Learning is critical to sustainable competitiveness in both blue collar and white collar work systems. Our literature review reveals that there has been a great deal of research examining knowledge seeking and sharing at the organization level but there have been relatively few studies focused on group learning. Understanding the operations of white collar work at the group and organization level will require more basic research into the mechanisms and support factors for group learning. We need better understanding of issues, such as how teams make learning decisions, how gained knowledge are shared and translated into team routines, and the interaction among knowledge properties (e.g., codifiability, completeness, and diversity (Turner and Makhija 2006)), team property (e.g., structural diversity) and learning. Moreover, due to the intellectual nature of the work, knowledge depreciation is a factor associated with learning in white collar systems, which can have a significant impact on work productivity (Park et al. 2006). For example, since the new developing tools update very rapidly, software engineers must keep learning those new products in order to work efficiently and collaborate with peers effectively. There has been some research on depreciation rate of technical knowledge (de Holan and Phillips 2004, Bosworth 1978, Park et al. 2006), which may be applicable to modeling learning and knowledge depreciation in white collar work systems.

7 Conclusion

The past several decades have witnessed a dramatic rise in the quantity and variety of white collar work. The growing need for white collar research has been addressed by scholars from various disciplines, including Sociology, Organizational Behavior, Marketing, Information Systems, and Economics. Although interest in white collar work is also on the rise within the Operations Management community, research into operational issues associated with white collar work is still very limited. Moreover, we lack frameworks for incorporating insights from other fields (e.g., the role of trust, social networks, motivation, learning, knowledge transfer, etc.) into OM models.

In this paper, we have attempted to address these gaps by providing a survey of the various streams of research relevant to white collar work. We have organized this review by focusing on white collar work at the level of the individual, team, and the organization. To help us classify existing research studies into these categories we have proposed a base model for each level of white collar work. These base models enable us to connect research from disparate fields to OM concerns. Furthermore, they enable us to identify gaps in the research coverage of the three categories of white collar work, and point toward specific research needs that are key to development of a science of white collar workforce management.

We hope that this survey will stimulate fundamental research on white collar work from an Operations Management perspective and provide a reference for scholars seeking to integrate research threads from different fields to improve our understanding of white collar work systems.

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