07-096

Toward a Theory of Behavioral Operations

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Draft: April 30, 2007

The authors gratefully acknowledge the financial support from the Harvard Business School Division of Faculty Research and Development. We thank participants at the MIT Sloan School OSG seminar for their insightful feedback on the ideas presented here. We are especially grateful to Amy Edmondson, Charles Fine, Robert Hayes, Richard Nelson, Andrew McAfee, Roy Shapiro, Noel Watson and Steven Wheelwright for their insightful comments on earlier drafts. Please address correspondence by email to fgino@andrew.cmu.edu or gpisano@hbs.edu.

ABSTRACT

Human beings are critical to the functioning of the vast majority of operating systems, influencing both the way these systems work and how they perform. Yet most formal analytical models of operations assume that the people who participate in operating systems are fully rational or at least can be induced to behave rationally. Many other disciplines, including economics, finance, and marketing, have successfully incorporated departures from this rationality assumption into their models and theories. In this paper, we argue that operations management scholars should do the same. We highlight initial studies that have adopted a "behavioral operations perspective" and explore the theoretical and practical implications of incorporating behavioral and cognitive factors into models of operations. Specifically, we address three questions: 1) What is a behavioral perspective on operations? 2) What might be the intellectual added value of such a perspective? 3) What are the basic elements of behavioral operations research?

Keywords: *Behavioral Operations; Decision-Making; Beer Game; System Dynamics; Cognitive Biases*

I. Introduction

The field of operations dates back to Frederick Taylor's time-motion studies in the early 20^{th} century. Since then, much has changed in the environment (technology, globalization, etc.), the nature of operations themselves (network structures, information systems, lean manufacturing, etc.), and the repertoire of tools available (capacity planning, inventory models, forecasting methodologies, project management methods, and so on). Yet one thing has not changed: in the vast majority of operations—from manufacturing and services to supply chains and R&D—people are a critical component of the system. As Hayes, Wheelwright, and Clark (1988) state:

> Superior performance is ultimately based on the people in an organization. The right management principles, systems, and procedures play an essential role, but the capabilities that create a competitive advantage come from people—their skill, discipline, motivation, ability to solve problems, and their capacity for learning (242).

The enduring importance of human behavior in operations suggests that people may significantly influence how operating systems work, perform, and respond to management interventions.

Most formal analytical models in operations management (OM) assume that the agents who participate in operating systems or processes—as decision-makers, problem solvers, implementers, workers, or customers— are either fully rational or can be induced to behave rationally. More specifically, these models assume that people can distinguish signal from noise, that they react to relevant information and discard irrelevant information, that their preferences are consistent, and that their decision-making process incorporates all relevant alternatives and variables and is unhampered by cognitive biases or emotions. According to the traditional OM literature, one way to achieve rational behavior is to increase monetary incentives; any irrationality, it is argued, is simply a matter of misaligned incentives. This solution, however, does not take into consideration the findings of behavioral decision research, such as the results of studies on trust (e.g., Malhotra, 2004) or reciprocity and fairness (Fehr, and Gächter, 2000; 2002; Fehr and Schmidt, 1999). While advances in the understanding of human behavior and cognition have begun to influence the fields of economics, finance, accounting, law, marketing, and, more recently, strategy, a “behavioral perspective” has largely been absent in the field of operations.

This has started to change with a growing number of experimental studies within OM, the majority of which has explored the behavioral underpinnings of the “bullwhip” effect (Croson and Donohue, 2002; 2006; Sterman, 1989a; 1989b; Croson, Donohue, Katok and Sterman 2005) or has investigated issues at the interface between operations and human resource management (for a thorough review, see Boudreau, Hopp, McClain and Thomas, 2003). More recent work from a system dynamics perspective has begun to shed light on how behavioral factors impede improvement in operations (see, for instance, Repenning and Sterman, 2002; Ford and Sterman, 1998; 2003a; 2003b).

In this paper, we build on these earlier studies to explore the theoretical and practical implications of incorporating behavioral and cognitive factors into OM models. We argue that differences in operations performance cannot be explained by existing operations models: only a careful examination of behavioral and cognitive factors can shed light on differences in operations outcomes and processes, such as productivity, efficiency and flexibility. Specifically, the paper addresses three main questions: 1) What is a behavioral perspective on operations? 2) What might be the intellectual added value of such a perspective? 3) What are the basic elements of behavioral operations research?

In addressing these questions, we structured the paper as follows. The next section describes the issues investigated by OM scholars and highlights the relevance of the human factor across these issues. In Section 3, we define a behavioral perspective on operations. In Section 4, we review some of the work in the emerging field of behavioral operations. We then describe a few anomalies encountered in the OM field that cannot be explained by existing theories (Section 5). We focus on anomalies encountered in a specific OM process, namely product development. The project management literature and the research on phase-gates processes are examples of areas in the OM field that tend to ignore behavioral aspects. Section 6 concludes by discussing the implications of adopting a behavioral perspective to study OM problems and by delineating potential areas for future work.

Our goal is to provide a precise definition for behavioral operations research, to highlight the inability of current OM models to predict systematic errors in OM settings and identify fruitful venues for future research. With this aim in mind, we describe both the intellectual terrain of operations management and behavioral decision research. We also summarize the work that has already been done in behavioral operation research and describe areas that would benefit from further investigation. With this paper, we hope to make OM researchers realize the importance of the human factor in explaining differences in operations performance. At the same time, we hope to make behavioral decision researchers realize that OM settings can be fruitful contexts to study judgment and decision making.

II. The intellectual terrain of operations management

Operations management is a multi-disciplinary field that investigates the design, management, and improvement of processes aimed at the development, production, delivery, and distribution of products and services (Weiss and Gershon, 1989). Research on operations focuses on explaining differences in *operating performance* across organizations (e.g. productivity, quality, product development lead times, etc) and, as a normative field, identifying the implications for processes, structures, and systems. Whereas historically OM focused mainly on manufacturing environments, the field today also covers issues pertinent to R&D, services, supply chains (logistics and distribution), and retailing. *Design* encompasses the specification of the various processes, policies, and strategies that constitute the overall operating system. Setting inventory policy, determining plant size and location, specifying a product development process, deciding which IT system to deploy, and creating incentive plans are just a few examples of common operating system design issues. *Management* refers to the decisions and actions that take place within the constraints imposed by the design of the operating system. It involves activities such as implementing policies, procedures, and strategies; making contingent decisions; coordinating processes; identifying and solving problems; responding to uncertainty and unforeseen problems; and motivating people. *Improving* the system refers to experimentation and learning activities geared toward enhancing operating performance over time.

Research on the design, management, and improvement of operating systems and processes is carried out through multiple methodological approaches, such as mathematical modeling, computer simulations, large sample empirical research, and field-based case studies. In addition to many methodologies, OM is also home to many disciplines, including applied mathematics, economics, computer science, engineering, and sociology.

Given its receptivity to many disciplines, it is somewhat surprising that explicitly behavioral decision theories and studies are still relatively rare within OM. This is perhaps due at least in part to the fact that OM has not rested upon a unified theoretical foundation. Other fields with such foundations have seen them so clearly challenged by behavioral research that the fields as a whole were moved to react.[1] Over the past decade, the study of human behavior has taken root in many fields, such as economics (with the rise of behavioral economics), finance (behavioral finance), and marketing (with an increasing focus on the psychology of consumer behavior). Scholars in these fields started to realize that relying exclusively on normative models and theories led to systematic errors in describing or predicting people's behavior (Thaler, 1980). These systematic and predictable errors are due to the fact that, when facing decisions (especially if such decisions are complex), people behave in ways that are inconsistent with available theories. Indeed, while normative theories generally assume that people are rational agent, actual behavior provides evidence for what Simon called "bounded rationality" (Simon, 1957: 198):

> The capacity of the human mind for formulating and solving complex problems is very small compared with the size of the problems whose solution is required for objectively

[1] In this paper, we use the term behavioral research broadly; in our definition, it includes both behavioral decision research (BDR) and judgment and decision-making research (JDM). BDR is an interdisciplinary field that draws on insights from psychology and economics to provide a descriptively more realistic picture of human decision making than that offered by traditional economic research. BDR focuses not only on deviations of real-world decision making from the stylized assumptions of economics, but also on ways in which human performance might be improved. As for JDM, it is an interdisciplinary field dedicated to the study of normative, descriptive, and prescriptive theories of decision making. The JDM literature borrows from and contributes to various fields, including economics, statistics, psychology, medicine, law, organizational behavior, and marketing.

> rational behavior in the real world – or even for a reasonable approximation to such objective rationality.

We explain how the idea of bounded rationality affected research in economics, finance and marketing next.

A closer look at human behavior in other fields

For many years, economists built their models on the assumption that individuals are rational. In particular, most economists assumed that individuals act *as if* their economic choices and decisions are rational. This perspective reached full bloom with the rational expectations revolution of the 1970s (see, for example, Lucas, 1972). The work of Simon (Simon, 1956; 1957) and Tversky and Kahneman (Tversky and Kahneman, 1974) clarified that human beings are limited in their capacities to learn, think, and act, and that these limits had important implications for economic theory. In particular, research has found that human beings are limited in their ability to process information (Simon, 1976). As evidence, various researchers have identified a large number of biases and heuristics over the past thirty years. Biases, which result from cognitive limitations, are systematic errors affecting people's decisions or judgments; heuristics represent rules of thumb that people commonly employ to navigate the ocean of information available to them in their decision-making process. Because of this evidence, in the past 20 years, economists have begun to accept that psychology plays an important role in describing and explaining people's behavior.[2]

In the case of finance, the theoretical foundation challenged by behavioral research has been the "efficient market hypothesis," which asserts that prices on traded assets in financial markets reflect all known information (including the collective beliefs

[2] For an overview of behavioral economics, see Camerer (1999) and Thaler (1980; 2000).

of all investors about future prospects) and are therefore accurate. A growing field of research, behavioral finance, studies how cognitive or emotional biases, which can be individual or collective, create anomalies in market prices and returns that may be inexplicable via the efficient market hypothesis alone (e.g., Shefrin, 2000).[3] Several studies have shown under what conditions and in what directions investors deviate from rationality. For instance, investors often fall prey to herding behaviors, making decisions based on what others have chosen (e.g., Shiller, 1984; Olsen, 1996). Investors also are fooled by randomness and underestimate its impact on their financial decisions (e.g., Taleb, 2001). They are overconfident and, as a result, they often trade much more than they should (e.g., Odean, 1998; 1999). They also often fall victim to the “attribution bias,” ascribing blame for negative outcomes to exogenous factors or other people and taking credit for positive outcomes (e.g., Barber and Odean, 2002).

Finally, in the field of marketing, long-held assumptions about rational choice and, in particular, consumer preferences have been challenged. Three assumptions about preferences underlie the rational theory of choice: preferences are complete (that is, the consumer is able to rank any two goods[4]); preferences are transitive (that is, the consumer makes choices that are consistent with each other[5]); and the consumer prefers more choices to fewer choices (because goods are assumed to be desirable and consumers are assumed to never be satiated).

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[3] For a comprehensive introduction to behavioral finance, see Shleifer (2000).

[4] For goods A and B, for example, the consumer can state her preferences according to one of the following possibilities: she prefers good A to good B; she prefers good B to good A; or she is indifferent between, or equally happy with, goods A and B.

[5] Suppose that a consumer tells us that she prefers good A to good B and good B to good E. We can then expect her to prefer good A to good E.

However, actual consumer behavior, like that of investors, often does not conform to theory. In fact, consumers are overwhelmed by too many choices. Specifically, social psychology research on “choice overload” shows that giving individuals too many choices reduces the quality of their decisions and sometimes leads them to give up and make no choice whatsoever (e.g., Iyengar, and Lepper, 2000). In particular, both experimental and field studies show that extensive choice may hinder the motivation to buy and decrease subsequent satisfaction with purchased goods, even if the purchase is initially appealing (e.g., Iyengar, and Lepper, 2000; Botti and Iyengar, 2004). Research also shows that being forced to make up reasons for a decision can lead to the abandonment of one’s intuitive sense of what is best and thus to a subsequent wrong choice (e.g., Wilson and Schooler, 1991). Scholars in the marketing field also investigated the impact of price on purchase. For instance, Gourville and Soman (1998; 2002) found that consumers’ attention to the cost of a product -- and the likelihood of the purchased item being used -- increases if payments occur at or near the time of consumption and decreases if payments occur long before or after the actual purchase. In other work, in their investigation of the effect of “price bundling” on product consumption, the researchers found that it increases short-term demand but often also reduces consumption (Soman and Gourville, 2001).

In contrast to economics, finance, and marketing, OM appears to be a multi-theoretical or even “atheoretical” discipline,[6] meaning that it lacks a dominant theory.[7] An analysis of more than 40 years of project management research, for example, found

[6] For instance, production thinking throughout the 20th century was dominated by three main theories: the transformation view (e.g., Starr, 1966), the flow view (first proposed by the Gilbreths, 1922, and first translated into practice by Ford, 1926), and the value generation view of production (initiated by Shewhart, 1931).

[7] In fact, there is no single dominant theory that might be considered as a target to question.

no clear "theory of project management" (Kloppenborg and Opfer, 2000). OM may not offer a single theory, but it does offer many prescriptions to practitioners. Yet to the extent that these prescriptions rest on models with ungrounded behavioral assumptions, their usefulness in practice might be limited. We argue that an explicit perspective that is *cognitively and behaviorally compatible* is crucial for the future of the OM field. Behavioral operations research is aimed at filling this gap. By investigating the human factor, behavioral operations research attempts to explain differences in operations processes and performance across firms that existing OM models fail to explain.

III. Behavioral operations: a definition

We define *behavioral operations* as an emergent approach to the study of operations that explicitly incorporates social and cognitive psychology theory. In particular, we define behavioral operations as the study of attributes of human behavior and cognition that impact the design, management, and improvement of operating systems, and the study of the interaction between such attributes and operating systems and processes.

Behavioral operations and traditional operations management share the same intellectual goal (the design, management, and improvement of operating systems and processes), but their research focus is different. In the operations management literature, human behavior traditionally has been either ignored or, at best, treated as a second-order effect. For instance, normative models developed in operations research (e.g., inventory theory, forecasting and scheduling models) typically assume that decisions are carried out by an idealized decision maker who is unfailing rational (Swamidass, 1991). By contrast, behavioral operations treats human behavior as a core part of the functioning and performance of operating systems—that is, as a first-order effect. Specifically, behavioral operations focuses on how cognitive and behavioral factors shape the way operating systems and processes work and perform and on the normative implications for the design, management, and improvement of these systems and processes.[8] In behavioral operations, the performance impacts of any given management intervention (e.g. a new tool, a new process, etc.) can not be predicted or explained without explicit reference to the underlying behavioral and cognitive factors at work in the operating system. At its core, behavioral operations explores the intersection of behavioral decision research, which is focused on human behavior, and OM, which is focused on system behavior. OM contexts are complex organizational settings where, very likely, individual biases interact and various decision makers use heuristics at different stages of the decision-making process. Operating problems, by their very nature, engage groups of people with various skills and organizational responsibilities and involve processes that are ongoing and dynamic, in the sense that the conditions and decisions made at one point in time affect the conditions experienced, the skills and resources available, and the actions that can be taken at a later point.

Another element adds complexity to this picture. In operations, two categories of inquiry need to be considered: 1) the properties of individuals, or the study of how cognition affects operations; and 2) properties of groups and organizations, or the study of how social norms and social systems affect operations. These properties are considered

[8] In the psychology literature, cognitive sciences and behavioral research belong to two very distinct fields. Cognitive science, the interdisciplinary study of mind and intelligence (e.g. Luger, 1994), embraces cognitive psychology, philosophy (especially the philosophy of the mind), linguistics, neuroscience, anthropology, computer science, and engineering. It is the study of the nature of various mental tasks and the processes that enable them to be performed. Behavioral research is here used to refer to studies in the field of psychology and sociology that focus on human behavior. For instance, cognitive biases are included under this label.

according to the areas of psychology most relevant to behavioral operations, namely cognitive psychology and social psychology.

Cognitive psychology studies the mental processes that underlie behavior, including thinking, deciding, reasoning, and, to some extent, motivation and emotion. These topics cover a broad range of research domains, examining questions about the workings of memory, attention, perception, knowledge representation, reasoning, creativity, and problem solving. Of particular relevance for OM are issues related to bounded rationality (Simon, 1956; 1957; Kahneman, 2003) and findings from studies on judgment and decision-making (e.g, Bazerman, 2005; Plous, 1993; Gilovich, Griffin and Kahneman, 2002).

Social psychology is the study of the nature and causes of human social behavior, with an emphasis on how people think about and relate to each other (Aronson, Wilson and Akert, 2004). Social psychology attempts to understand the relationship between minds, groups, and behaviors in three primary ways. First, it examines how the actual, imagined, or implied presence of one or more people influences the thoughts, feelings, and behaviors of individuals. Topics within this area include social perception, social interaction, and the many types of social influence, including trust, power, and persuasion.[9] Second, social psychology examines the influence that individual perceptions, beliefs, and behaviors have upon the behavior of groups; this area has led to research on group productivity in the workplace and group decision making. Finally, social psychology tries to understand groups as behavioral entities, as well as the

[9] The research in these areas focuses on the influences that individuals have on the beliefs, attitudes, and behaviors of other individuals, as well as the influence that groups have on individuals.

relationships and influences of one group upon another group. Of particular relevance for OM are issues related to equity and fairness, trust and reciprocity, and attributions.

In addition to research on small groups, of particular importance to behavioral operation research is work on organizational behavior (for an overview of the field and research contributions see Thompson, 2003; Shapira, 1997). Indeed, operations often take place in the context of large organizations. Issues such as organizational culture, organizational design and structure, organizational communication and learning are of crucial importance.

The findings of these two areas of psychology have not yet made their way into the OM field. Indeed, the overwhelming majority of research articles published in OM utilizes analytical frameworks that assume a high degree of rational decision-making. Moreover, many practice-oriented frameworks of OM, while somewhat more flexible, still ignore (or minimize) the impact of human behavior and, consequently, the systematic biases that affect it. Yet it is possible to identify OM research that has adopted a behavioral perspective. We review it next.

IV. Behavioral research in operations management

While it is probably premature to discuss behavioral operations as if it were an existing field, behavioral considerations have been prominent in a number of OM investigations. The earliest of these, in fact, are almost as old as the OM discipline itself. Research conducted by Mayo, Roethlisberger, and Dickson in the 1920s and 1930s (see, for instance, Ross and Nisbett, 1991: 210-212) examined the physical and environmental influences of the workplace (e.g., brightness of lights, humidity) as well as the psychological aspects (e.g., breaks, group pressure, working hours, managerial leadership). The major finding of the study was that, almost regardless of the experimental manipulation employed, worker production seemed to improve, leading to the conclusion that the workers were pleased to receive the researchers' attention and interest.[10] Along with Frederick Taylor's work, this study gave rise to the field of industrial psychology but did not result in a new approach to the study of OM.

In fact, only recently have OM scholars begun to pay attention to insights from psychology. Part of this research was probably stimulated by Boudreau et al.'s paper (2003), which emphasized the importance of incorporating behavioral factors into OM work (Bendoly, Donohue and Schulz, 2006). In their article, Boudreau et al. highlight the relevance of considering both technical and human aspects when investigating operating systems and their performance and provide an organizing framework which includes both human resource management and operations management factors. In so doing, the authors discuss the common assumptions researchers make when modeling human behavior in OM settings. Some of their assumptions (e.g., workers are emotionless, deterministic and predictable) could be summarized by labeling people as boundedly rational. Such recognition, together with the realization that people play a major role in explaining differences in operating performance, is the core assumption of behavioral operations research.

Based on our definition of this emerging field, a behavioral perspective on OM problems can be found in two streams of prior research. The first uses experiments to investigate the causes of OM phenomena. Much of this research has focused on the "bullwhip effect" in supply chains (see, for instance, Lee, Padmanabhan and Whang,

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[10] After this series of studies, the Hawthorne effect is a label used to refer to an increase in worker productivity produced by the psychological stimulus of being singled out and made to feel important.

1997) and has used “beer distribution game” simulation (see Croson and Donohue, 2002). As part of this research stream, a recent review by Bendoly, Donohue, and Schulz (2006) identified several studies that used laboratory experiments to study phenomena or factors relevant to OM. Building on the work by Boudreau et al. (2003), this thorough review piece also provides a framework that can be used to identify behavioral assumptions commonly used in OM analytical models. While this framework is helpful for identifying OM problems that could be better explained or investigated through a behavioral lens, it is limited in the fact that the focus is only on work employing an experimental approach. As we will discuss later in the paper, we believe that multiple approaches can and should be used to contribute to behavioral operations research.

The second stream draws from system dynamics to simulate the impact of behavioral forces on the dynamics and performance of various operating systems, including supply chains and product development (e.g., Repenning and Sterman, 2002; Ford and Sterman, 1998; 2003a; 2003b).

In the next sections we focus on these two main streams of research. Our goal is not to provide a complete review of the literature but to describe some of the important work that has been done to date in behavioral operations research. Such work is used as an example of what can be learned by adopting a behavioral perspective in OM and of the various approaches that can be used. We chose these two streams of research since they help us make the case that currently available OM models are incapable of explaining a series of anomalies observed in OM settings.

The bullwhip effect in supply chains and the use of experiments in OM

The bullwhip effect. The "bullwhip" effect is an empirically documented phenomenon affecting supply chains: As demand for a product, filtered by product ordering decisions, move upstream in the chain from the consumer toward the manufacturer, that demand becomes more and more erratic and swings in larger and larger cycles (see, for instance, Lee *et al.* 1997).[11] Several empirical studies have explored the *operational* causes of the bullwhip effect and identified four factors: demand forecast updating (Chen, Drezner, Ryan, Simchi-Levi, 2000), order batching (Baganha and Cohen, 1996), price fluctuation (Sogomonian and Tang, 1993), and rationing and shortage gaming (Cachon and Lariviere, 1999). Related work has focused on *behavioral* causes of the bullwhip effect, such as cognitive limitations and the inability to coordinate (Forrester, 1958, 1961; Sterman, 1989a, 1989b; Croson, Donohue, Katok and Sterman, 2005; Watson, and Zheng, 2005a), based on the argument and demonstration that the effect persists even if all operational causes are removed, even in the case of constant and known demand. Behavioral factors have been explored through experimental studies using the beer distribution game, an exercise that showcases the problems that arise in a company with minimal communication in the supply chain.[12]

The use of experiments in OM. The bullwhip effect represents an interesting example of an area in which experimental methods have been used to study operations problems, in this case with a specific focus on supply-chain management. There are a

[11] These swings in demand often create excess capacity, excess inventories, and poor customer service in the supply chain, as myopic producers and suppliers seek to deal with them. To counteract the bullwhip effect, firms must modify the supply chain's infrastructure and related processes (Lee *et al.*, 1997).

[12] The game is a simulation of a supply chain with four agents: retailer, wholesaler, distributor, and factory. Participants take the role of an agent and decide, based on their current stock situation and customer orders, how much to order from their suppliers. All agents have a common goal: minimizing costs for capital employed in stocks while avoiding out-of-stock situations.

few other examples in which laboratory studies have been used in OM applications (for a complete and thorough review, see Bendoly et al., 2006). Here we focus mainly on research which was not discussed in length in previous reviews of behavioral operations research (see Bendoly et al., 2006; and Boudreau et al., 2003). The first is provided by the service-provider choice experiments (Gans, Knox, and Croson, 2005), which aim to evaluate the performance of the different models that consumers use when choosing among suppliers.

The second application refers to the newsvendor problem, a fundamental building block for models of inventory stocking in the face of stochastic demand (Porteus, 1990) and, at a broader level, for models of supply chain systems (Cachon, 2002). The prescriptions resulting from these models typically assume that the newsvendor will stock optimally. Yet, in a laboratory setting that generated predictions of optimal orders and compared actual orders to optimal orders, Schweitzer and Cachon (2000) found that many people make suboptimal and biased newsvendor choices.[13] Building on this work, Bolton and Katok (2005) investigated experimentally whether enhancements to experience or feedback can improve newsvendor problem decisions by promoting better learning-by-doing. They found that how experience and feedback are organized for the decision maker may have a relevant impact on whether inventory is stocked optimally (Bolton and Katok, 2005). In an attempt to explain suboptimal behavior in ordering decisions, Bloomfield, Gino and Kulp (2007) take a step toward unifying the newsvendor and bullwhip literatures. By using an experimental approach, the authors investigate the effects of product durability, time lags and demand shocks on ordering decisions. Their

[13] In particular, they found that subjects ordered more high-profit than low-profit goods but under-ordered high-profit relative to optimal goods and over-ordered low-profit relative to optimal goods. They also observed little or no change in ordering over time, meaning that learning seemed not to occur.

results suggest that the bullwhip effect may not be driven entirely by the inter-firm dynamics that arise when firms interact in a supply chain.

Lastly, OM researchers have used experiments to explore potential behavioral influences through the study of the "secretary problem" (Ferguson, 1988), a mathematics puzzle, suited to laboratory experiments, that represents a class of real-world sequential decision-making tasks. In the secretary problem, subjects are presented sequentially with a known number of items of varying quality. They must select the best item from those on offer; rejecting an item is irrevocable.[14] Several empirical studies have applied the secretary problem to economic decision making (e.g., Kogut, 1990). Seale and Rapoport (1997), for instance, focused on the evaluation of plausible heuristic models of human decision-making.

These examples of experimental OM research have been used to test existing OM theories, with a particular focus on optimal policies in supply-chain models (e.g., inventory management and optimal ordering rules). The assumptions of theory have been implemented in the lab so that point predictions and outcomes could be compared in a controlled environment. Such experiments allowed researchers to explore the reasons why behavior deviates from theories and produces results that are not optimal and to design treatments that might reduce those deviations.

System dynamics models in operations contexts

A second stream of behavioral work in operations includes studies that incorporate system dynamics models. System dynamics is an approach to modeling the

[14] The canonical example is an organization wishing to hire a secretary. Applicants present themselves sequentially; the interviewers may rank the applicants, and can remember the quality of everyone whom they have interviewed. However, if an applicant is rejected, that person will find another job and become unavailable for hire.

dynamics of complex systems such as populations, ecologies, economies, organizations, and operating systems.[15] It focuses on examining the feedback loops that interact and influence the way a system behaves over time.

This approach has been used to study operational or organizational improvement (Repenning and Sterman, 2002; Sterman, Repenning and Kofman, 1997), innovation implementation (Repenning, 2002), and product development (Ford and Sterman, 1998; 2003a; 2003b). It has been particularly adept at incorporating behavioral factors as part of the feedback loops that influence operational system performance. For instance, Repenning (2002) investigated the dynamics of innovation implementation, focusing specifically on how organizational factors might limit the effectiveness of such implementation. He found that the failure of potentially useful innovation results not from an intrinsic lack of efficacy, but instead from a lack of commitment and skill needed to use the innovation and their dynamic interaction with several forces within the organization over time (Repenning, 2002). In another paper, Repenning explored the nature and causes of firefighting in product development (Repenning, 2001).[16] He suggested that, after a tipping point determined by resource utilization, firefighting becomes a self-reinforcing phenomenon whose persistence is due to both structural and psychological factors.

A common theme emerging from the system dynamics studies is that the performance of operating systems over time is a function of the interaction of both the physical or structural elements of the system (e.g., time lags, activity durations, the

[15] For details on the system dynamics approach see Sterman, 2000.
[16] "In the product development context, firefighting describes the unplanned allocation of engineers and other resources to fix problems discovered late in a product's development cycle" (Repenning, 2001, p. 287).

physical structure of the product development process) and the behavior of individuals operating within the system (e.g., decision rules used by participants within the development process and biases affecting those decisions). For instance, the critical driver of the success of process-focused improvement efforts (e.g., the implementation of TQM) is the interaction between the physical structure of the workplace and attribution biases in determining who or what was responsible for the poor organizational performance (Repenning and Sterman, 2002).[17] In essence, the studies in this second stream of work suggest that performance problems in operations are as much a function of behavioral factors and cognitive biases as they are a function of structural factors.

Behavioral research in operations management: Summary

The two research streams discussed above highlight the role of behavior and cognition in operating performance and provide examples of research in behavioral operations. In particular, these studies suggest that taking behavioral and cognitive factors into account can lead to fundamentally different predictions about the performance of given operating systems under specific conditions. By focusing on the interaction and feedback among technical, organizational, and behavioral features of OM systems (Ford and Sterman, 2003a), they also identify a different root cause of many operating performance problems and thus suggest different managerial interventions.

Yet, this prior research has not identified all of the pathologies characterizing the OM field, which are poorly understood when examined with existing OM theories. We provide further examples of unexplained OM anomalies in the next section.

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[17] In attribution theory, the fundamental attribution error is the tendency for people to over-emphasize dispositional, or personality-based, explanations for behaviors observed in others while under-emphasizing the role and power of situational influences on the same behavior (see Heider, 1958; Ross, 1977).

Before doing so, it is worth mentioning two other streams of research that might be considered part of behavioral operations, namely the “socio-technical” view within technology management (also known as sociotechnical systems theory; see Cherns, 1976; Eason, 1988) and the approach of human factor engineering (see Vicente, 2006; Norman, 1988). We summarize them briefly below. Researchers interested in behavioral decision research should indeed get acknowledged with these streams of work too.

Socio-technical view of technology management. According to this view, physical technologies are socio-technical systems comprised of humans, human activity, spaces, artifacts, tools, and communications media. This theory suggests that a change in the technology and techniques of work (the way in which work is done) impacts social interactions in the workplace; thus, changing the technical system without attention to the social system can lead to unintended consequences (Huber and Brown, 1991). The literature includes discussions of induced change (see, for instance, Van de Ven and Poole, 1995), goal commitment (Locke, Latham and Erez, 1988), motivation (Steers and Porter, 1991), implementation (Klein and Sorra, 1996), and institutionalization (Goodman, Bazerman and Conlon, 1980). As part of this stream of research, several scholars have focused their attention on a specific technology, i.e. computer technology (see, for instance, DeSanctis and Poole, 1994; Orlikowsky, 1992; 1996; 2000).

What appears to be missing in this stream of research is an exploration of *cognitive biases*, which might explain (at least partially) the difficulties and failures encountered in technology implementation discussed in this literature.

Human factor engineering. Research in human factor engineering investigates topics such as human performance, technology, design, and human-computer interaction.

Specifically, human factor engineering researchers focus on how people interact with products, tools, procedures, and any processes likely to be encountered in the modern world (a detailed discussion of this approach and examples of its benefits can be found in Vicente, 2006; see also Norman, 1988). While the current quickly-changing technologies have increased the interest in this field, its origin dates back to the design and use of aircraft during World War II aimed at improving aviation safety. In a nutshell, human factor engineering involves working to make products, technologies and the environment function in a way that seems natural to people and thus reduces human error.

Related research has investigated possible explanations for accidents when complex technological systems were involved (see, for instance, Perrow, 1999). In this case, researchers suggest that the conventional engineering approach to ensuring safety tend to make accidents more likely by increasing the complexity of the system (through the addition of warnings or safeguards).

While the field of human factor engineering mostly focuses on the design of products and technologies, we believe that systematic errors affect people's decision making and interaction with operating system also at the level of management and improvement of those systems. Thus, while building on the insights coming from human factor engineering studies, behavioral operations researcher should explore the impact of the human factor in all the aspects involved in an OM system: not only design, but also management and improvement.

V. From OM anomalies to better-informed OM theories

Research in the OM field tends to be normative and focused on prescribing how operating systems and processes *should* work. The main concern is the identification of the appropriate principles, processes, and structures needed to make the system work in the optimal (that is, most efficient and most effective) way. As a result, OM theories provide normative prescriptions and models that, if followed, should assure an optimal functioning of the systems and processes in the areas of design, management, and improvement. Yet, these models are often not considered very useful by those who are supposed to use them. For instance, the decision-theoretic models proposed in the literature to deal with R&D portfolio decisions are highly complex and, as a result, have not been commonly used in management practice (Loch and Kavadias, 2002). We suggest that practitioners recognize what OM researchers have largely ignored: real operating systems (factories, supply chains, product development organizations, etc.) are complex social systems where human behavior is a central actor, and thus the usefulness of tools, methods, and frameworks that ignore this fact is limited.

OM as taught and practiced today rests on models and theories that can be enriched by descriptions of how operating systems and processes *do* work. Behavioral operations research starts with grounded assumptions from cognitive and social psychology; it recognizes that people have cognitive limits and, as a consequence, their decisions might be hampered by systematic biases. Only after taking these limits and characteristics into account does behavioral operations research consider how to design, manage, and improve operating systems and processes. We suggest that a deep understanding of how operating systems and processes actually work is needed to provide a basis for building tools and models for designing, managing, and improving them. This understanding will not only incorporate more realistic assumptions into OM models, but also generate more useful prescriptions and implications for both research and management practice.

The rationale for a behavioral approach to operations should be improved insight into and understanding of problems. In finance and economics, for example, behavioral theories began to gain traction because they offered explanations to empirical regularities that were considered anomalies when viewed through existing theoretical lenses. Anomalies provide a useful starting point for the construction of new theory. A behavioral theory of operations must do a better job at explaining how operating systems work, and how they can be improved, than existing theories. If not, there is no intellectual motive for an alternative approach.

As noted above, the bullwhip effect in supply chains is an example of one such anomaly that was better explained through a behavioral lens. There may be many others, but we will highlight two anomalies that, based on our own and others' research, could represent the same type of opportunity. We draw from examples in product development. Our choice is not random. These are the areas closest to our own research in OM and thus the place where we have the best grasp of the particulars, but also where we have been forced to grapple with the gap between existing OM theory and the empirical regularities. The two anomalies we examine are the tendency of product development projects to run late and the problem of managing portfolios of R&D projects (and project selection).

The traditional approach to these two problems is to develop better models for project management and more sophisticated in-process management tools (such as real-time scheduling and earned-value progress charts) and to undertake more planning activities. We suggest that these models will be more useful if they rest on cognitively and behaviorally compatible assumptions. This means incorporating into the models elements that will reduce or possibly eliminate common cognitive biases that people incur in their decisions.

Why do product development projects always run late?

The first anomaly has to do with product development project performance. One of the most vexing management problems in product development is the tendency for projects to run late and over-budget. For instance, Ford and Sterman (2003a, 2003b) use the term “90% syndrome” to describe “a common concurrent development problem in which a project reaches about 90% completion according to the original schedule but then stalls, finally finishing about twice [the time] the original project duration has elapsed” (Ford and Sterman 2003b, p. 212). The phenomena has been documented in numerous case studies and examples (e.g. Cohen, Eliashberg and Ho, 1996) and widely discussed in the product development literature (e.g. Wheelwright and Clark, 1992).

Several studies in the OM literature have investigated the issue of improving timeliness and predictability in product development. Many prescriptions and formulas have been offered (see, for instance, Crawford, 1992; Gold, 1987). Most of this work has explained lateness in product development with the uncertainty inherent in development processes. At any of the stages of R&D, indeed, product development managers are asked to evaluate the available information about currently-under-development products and based on such information make decisions about whether or not to continue development. As many case studies have shown (e.g., Gino and Pisano, 2006a; 2006b), product development decisions are made under uncertainty, they are far from perfect and are affected by behavioral factors (such as sunk costs, escalation of commitment or even emotions).

To deal with uncertainty, OM scholars have developed tools and suggested approaches to better manage product development. These suggestions include the use of experimentation to resolve uncertainty early in the development process (e.g., Thomke, 2003), the use of parallel versus sequential sequencing of product development tasks (e.g., Loch, Terwiesch and Thomke, 2001), the use of cross-functional or heavy-weight teams (Clark and Fujimoto, 1991) or the utilization of standardized project management tools like 3-point estimation techniques. In sum, OM research has tackled the lateness problem in product development by suggesting better tools, processes or organizational structures.

One of the puzzles behind the lateness problem, which should make one suspect of the uncertainty explanation, is that project duration is not symmetrically distributed. If true uncertainty were at work, then in fact, we would expect to see (and hear about) projects which were both late and early. The asymmetric nature of duration suggests other factors may be at work. Furthermore, case study research suggests that behavioral factors may underpin the lateness problem (see e.g. Gino and Pisano 2006a, Pisano et al 2005) Extant behavioral literature provides a rich trove of possible underlying explanations for project lateness, including *the planning fallacy* (e.g., Buehler, Griffin, and Ross, 1994; 2002), *wishful thinking* (e.g., Babad, 1987; Babad and Katz, 1991), and *overconfidence bias* (Einhorn and Hogarth, 1978; Fischhoff, Slovic and Lichtenstein, 1977; Oskamp, 1962; 1965).

Most research on product development, while at least implicitly recognizing the role such behavioral forces may play, do not come directly to grips with how product development process should look in light of them. From a behavioral operations approach, a researcher would *start* with the assumption that these factors are present, and then ask what tools, methods, processes, or organizational structures are mostly like to ameliorate their potential negative effects. If you assume, for instance, that decision makers (e.g. project managers) are prone to overconfidence bias would the same decision tools and development processes traditionally advocated in the product development literature still be useful? Our sense is the answer is no. However, to the best of our knowledge, there is no research that explores this issue either theoretically or empirically.

Why do organizations always over-commit their R&D resources?

The second anomaly is that organizations over-commit to product development projects. Case study evidence suggests that many organizations have many product development projects in progress above their capacity. For instance, Wheelwright and Clark (1992) suggested that companies often operate their development organizations at 200-300% capacity utilization. Here again, there is a wide range of tools developed within OM research to help managers deal with the portfolio problem, and to make more rational allocations of resources (e.g. Kavadias and Loch, 2004).

As above, one must question whether, in fact, the problem is the lack of appropriate tools or methods to manage the process. In product development situations, the decisions of which project to work on and, subsequently, which projects to continue or abandon are potentially influenced by biases and emotions. Given that the evaluation of an uncertain project generally must rely on at least some subjective judgments by the decision maker, the interference of various biases and emotions in those subjective judgments can be difficult for the decision maker to detect (Chi, Liu and Chen, 1997). This type of limitation to rationality has been the focus of study in what is known as the escalation of commitment research in social psychology (Staw, 1981). Studies conducted in this stream of research have shown that people tend to make different decisions about whether to abandon an uncertain investment project when they are given the same ambiguous information about the project without being told the correct decision rule. Furthermore, people's investment decisions are subject to the influence of emotional factors (Strube and Lott, 1984).

The escalation of commitment has been found to be relevant also in product development settings. Schmidt and Calantone (2002) tested whether factors unrelated to a new product's forecasted performance cause managers to continue product development projects into subsequent stages of development at rapidly accelerating costs. They found that managers who initiate a project are less likely to perceive it is failing, are more committed to it, and are more likely to continue funding it than managers who assume leadership after a project is started (Schmidt and Calantone, 2002)

Together with escalation of commitment, overconfidence in estimating product development teams' capacity to work on various projects and planning fallacy, other systematic biases could explain the over-commitment anomaly, including *inaction inertia* (Tykocinski and Pittman, 1998; Tykocinski, Pittman, and Tuttle, 1995) and *procrastination* (Akerlof 1991).

The question, as before, is whether we would design project selection and portfolio management processes the same way, or use the same tools (e.g. real option valuation) if we started with an assumption that our decision-makers were prone to these deviations from rational behavior. And as before, one can only guess at the answer because there has been no systematic research on these issues.

The role of uncertainty in product development

Before concluding, we want to make a more general comment regarding decisions under uncertainty in product development. As Adler, Mandelbaum, Nguyen and Schwerer (1995) noted, “whereas uncertainty is an inherent characteristic of product development, current models and methods are essentially deterministic and do not account adequately for the impact of stochasticity on development cycle time” (p. 459). While uncertainty is a core feature of product development, project management and R&D, OM models aimed at improving R&D decisions do not take into account what is know in behavioral research about the biases affecting people’s evaluation of uncertainty. People use heuristics that, although valid in some circumstances, can lead to systematic errors with serious implications (Bazerman, 2005). We discuss the main heuristics people use when dealing with risk next, together with implications for product development decisions.

Availability. One of the heuristic which is relevant for risk perception is availability (Tversky and Kahneman, 1974). An event is judged as likely or frequent depending on the easiness people experience in imagining or recalling it. Rare events are generally more difficult to imagine or recall than frequently occurring events. While availability is the appropriate cue in certain circumstances, in many others is not. Furthermore, elements which are not related to the frequency of occurrence of an event have been shown to affect the availability heuristic. So, for example, managers overreact to the outcome of the last decision in competitive bidding (Montgomery and Weinberg, 1973). Thus, the use of the availability heuristic might reduce the openness and objectivity of risk discussions (Barnes, 1984) that take place in product development settings.

Consider a manager or leader in a product development team who wants to convince his team members of the benefits of developing a certain project by highlighting the improbability of alternative actions (e.g., working on different projects). By pointing out how other projects might fail, the manager might induce the audience to focus on the low-probability outcomes ("so many other projects failed; this will fail too") and thus end up with little support for the development of the project he is advocating.

Representativeness. A second heuristic discovered by Tversky and Kahneman (1974) is representativeness: the concept that an outcome is highly representative of the process from which it comes. Essentially, the more object X is similar to class Y, the more likely people think X belongs to Y. Thus, people tend to predict the outcome that they perceive as most representative of the available evidence, no matter what the reliability of that evidence is. For product development managers, these findings suggest that R&D decisions may not reflect the reliability of the available evidence. Mangers might fail at integrating different sources of information about the success of a project. For instance, in pharmaceutical companies, evaluations of projects are available from different teams including marketing managers, finance people and scientists. In such context, representativeness might hinder the optimality of decisions.

In addition, managers involved in product development activities such as planning and product management can often be supplied with selectively biased data (Barnes, 1984). For example, as noted by Barnes (1984: 132), "when operating managers perceive indices of relative share dominance and unit growth as critical to obtaining resource allocations they tend to manipulate product-market boundaries to qualify for resources (…). Unfortunately, the quality of review procedures followed by many firms through the planning cycle is rarely rigorous enough to successfully challenge all possible data distortions."

Anchoring and adjustment. A third heuristic affecting decision making processes under uncertainty is anchoring and adjustment: the idea that initial estimated values (anchors) affect the final estimates, even after considerable adjustments. Since its discovery (Tversky and Kahneman, 1974), this bias has been shown to occur in situations as diverse as general knowledge issues, probability estimates, legal judgment, pricing decisions and negotiation (Mussweiler and Strack, 2001).

Product development and project management both require managers to make estimates about the length of the development process and its various stages for each product or project under development. Often, these estimates are made while evaluating past performance or information about competitors' development efforts. Both elements could serve as anchors and lead to suboptimal decisions. For instance, Aranda and Easterbrook (2005) showed that the anchoring and adjustment heuristic takes place in software estimation processes: When estimators are given a high anchor their estimates are significantly higher than when they are given a low anchor or no anchor at all.

A large number of persistent biases. In the previous paragraphs we discussed the main heuristics affecting people's decision making under uncertainty. We also discussed systematic errors that might explain two common product development anomalies.

Several other biases have been investigated in the behavioral decision research literature and could be at the root of well-known OM anomalies.

We believe the main task of behavioral operations is to investigate the effects of these biases on operating performance and to explore potential interventions that address these biases. In traditional operations, researchers develop models or tools on the assumptions that decision makers are fully rational. If used properly, it is argued, such models will improve operating performance. Behavioral operations, instead, starts with the assumptions that decision makers are boundedly rational and their decision making processes are affected by systematic errors. Based on this assumption, behavioral operations researchers develop models or tools which take human cognitive limitations into account and thus create interventions that help to correct or counter-act the effects of biases. Human psychology cannot be changed; but operating systems can be designed in such a way that systematic errors are eliminated or at least reduced.

VI. Conclusions and future research

Research in psychology over the past several decades teaches us that behavioral biases and cognitive limits are not just noise; they systematically affect (and often distort) people's judgment and decision-making. Yet, the implications of these forces for the design, management, and improvement of operating systems is barely understood. We have identified two main areas for intellectual value added by behavioral operations. First, a behavioral approach to OM can lead to a better understanding of underlying drivers of operating system performance and also to a better understanding of puzzling "pathologies" (e.g., excess inventory, late product development projects, over-commitment to R&D projects, etc.). Second, a behavioral perspective can lead to a better identification of appropriate management interventions. For instance, the knowledge that behavioral issues have caused a company to carry too much inventory precludes the search for a better optimization algorithm. Thus, to overcome the psychological distortions at the root of many OM problems, behavioral operations research should consider ways to create "cognitive repairs" (Heath, Larrick and Klayman, 1998), or organizational practices that may solve the cognitive shortcomings of individuals within the organization (Heath *et al.*, 1998).

Future paths for research

We suggest that five types of behavioral operations research can and should be pursued: replication studies, theory-testing studies, theory-generating studies, adaptation studies, and OM-specific studies.

Replication studies refer to research that attempts to replicate or test existing behavioral theories with data from OM contexts. This type of research uses behavioral decision-making theories and findings from the psychology literature as a starting point. Can those theories and findings be replicated in OM contexts, or will their nature change? For instance, one might consider the impact of sunk-cost effects on project portfolio decisions or product development choices. Sunk costs are those that have already been incurred and that cannot be recovered. Economists argue that, if people are rational, they will not take sunk costs into account when making decisions. Yet, several experimental studies on individual decision-making have shown that people's economic behavior is often influenced by the sunk-cost fallacy (Arkes and Blumer, 1985; Garland, 1990; Heath, 1995; Thaler, 1980). Do sunk-cost effects influence project termination decisions?

What is the impact of costly prototyping on decisions in product development? Explorations of these questions would constitute replication studies.

Theory-testing studies aim at examining OM theories in a laboratory setting. Like experimental economics research, theory-testing studies should have three purposes: a) normative, aimed at designing laboratory experiments mimicking settings where theories make predictions; b) descriptive, or designed to test behavior and explain deviations caused by psychological forces; and c) prescriptive, aimed at suggesting debiasing techniques that can be used to reduce or eliminate systematic errors observed in people's behavior. The stream of research on the bullwhip effect and on the use of experiment in OM, discussed in Section 4, belongs to this second category. Many other OM theories could be tested as part of this type of behavioral operations research.

The third type of research in behavioral operations consists of *theory-generating studies*. In 1963, Bowman investigated aggregate production and employment scheduling and offered a method of "starting with the managers' actual decisions and building on them to reach a better system" (Bowman, 1963: 310). For several decades, however, this view has been almost completely ignored. Theory-generating studies would build on existing mathematical OM models, addressing the same problems but with changed assumptions formulated based on managers' actual decisions and biases. An example of this type of research comes from behavioral economics. Standard dynamic models of economics commonly assume that agents have the same discount rate at any time, whether beginning in the present moment or in the future. But empirical evidence shows that people's preferences are not consistent over time (e.g., Loewenstein and Prelec, 2002). To fit this psychological evidence, behavioral economists have started building their models with the assumption of hyperbolic discounting (e.g., Laibson, 1997). A second example comes from the OM field. Using formal models, Watson and Zheng (2005b) studied managers' overestimation of the permanence of new demand levels in the context of inventory replenishment and how error affects the behavior and performance of a single location inventory system.

The fourth type of research in behavioral operations consists of *adaptation studies*. In this case, the research originates from OM problems, phenomena, or puzzles and focuses on potential behavioral explanations. The stream of research on system dynamics models applied to operational contexts, discussed in Section 4, belongs to this third category. Other OM phenomena that could be explored under this rubric includes inventory record inaccuracy, or discrepancies between inventory records and physical inventory—a major obstacle to improved operational performance (Kok and Shang, 2005). While companies have undertaken large investments to automate and improve their inventory management processes, inventory records and physical inventory are rarely aligned. Inventory inaccuracy might result from factors such as stock loss or shrinkage, transaction errors (in the inbound or outbound processes), and misplaced products (Piasecki 2003; DeHoratius and Raman 2004; Raman, DeHoratius, and Ton, 2001). A behavioral perspective might reveal new insights into the causes of inventory inaccuracy and misplacement.

Finally, *OM-specific studies* are a fifth opportunity for behavioral operations research. These studies use mixed methodologies, such as lab experiments, field-based research, modeling, and empirical analyses to investigate important OM problems. For example, field research can be used to generate hypotheses to test in the lab. The main purpose is to potentially uncover new behavioral or cognitive factors that tend to arise in OM contexts. An example of this type of research is given by Edmondson's work on psychological safety (Edmondson, 1996; 1999), or "the shared belief held by members of a team that the team is safe for interpersonal risk-taking" (Edmondson, 1996). Within a work team, psychological safety facilitates learning behavior because it reduces an individual's concern about others' reactions to actions that might be embarrassing or threatening (Edmondson, 1999). This bias was uncovered in research in the operating context of medical errors; it was found in a field study investigating the ability of healthcare organizations to learn from failures occurring in the care-delivery process. Discovering the psychological safety bias in the laboratory would have been much harder, if not impossible.

Ultimately, multiple approaches will be required to unlock our understanding of how operating systems work and, in particular, how the social, human, and physical components of these systems interact. This perspective represents a significant broadening of the research agenda in operations. There is perhaps no agenda for the field more important than a deeper understanding of the behavioral and cognitive forces shaping operating systems and processes and the implications for the design of appropriate management tools and practice.

How to successfully contribute to the behavioral operations research field

In the previous sections we discussed several types of behavioral operations research that we believe are worth pursuing. We turn briefly to pragmatic issues of how behavioral decision research can be best incorporated in the OM field and strategies that can be used to accomplish this goal.

The first strategy is aimed at improving awareness within the OM field of the importance of behavioral and cognitive factors in operating performance. This strategy can be implemented through the usual methods of disciplinary cross-fertilization in academia such as symposia that bring together researchers from both fields. In addition, researchers from OM could regularly attend behavioral research oriented conferences (such as the Society of Judgment and Decision Making Conference or the Behavioral Decision Research in Management Conference). And OM departments who regularly have seminar series during the academic year could invite behavioral decision researchers to give talks.

A second strategy is collaborations between scholars in different fields (for instance, a “straight” OM person and a “straight” behavioral researcher) or scholars interested in behavioral operations research and with a background in either OM or BDR.

Finally, a third strategy is to train Ph.D. students who are part of OM or OR programs in behavioral decision research. While the core of their coursework should remain OM, these students could take introductory courses in organizational behavior, decision making and experimental methods.

Perhaps the biggest challenge for behavioral operations, like any emerging sub-field, is to gain legitimacy. Such legitimacy can only be earned by shedding new light on important phenomena in operations. Behavioral operations cannot simply be an exercise in “intellectual arbitrage,” porting well known concepts from field into another. There are many theoretical and experimental insights from behavioral research in other fields, but understanding the implications of those insights for designing, managing, and improving complex operating systems is no trivial task. We know many things now about such biases as sunk costs, framing and planning fallacy to mention just a few, but how those affect the behavior and performance of operating systems is largely unexplored. This will require the development of novel conceptual insights. And, this is a task that only researchers in operations management, who understand the complexities of actual operating environments and systems, can tackle.

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