Bodies of knowledge for research in Behavioral Operations

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Abstract

Whenever intrepid researchers venture into new terrain, they find that they require knowledge outside of their formal training. This paper reviews bodies of knowledge for OM researchers interested in the new area of Behavioral Operations. We highlight theoretical constructs and empirical phenomena from cognitive psychology, social psychology, group dynamics and system dynamics. We also provide a guide for where to go to learn more about each body of knowledge. Our overall goal is to lower the startup costs for new researchers in Behavioral Operations.

Keywords

heuristics, biases, motivation, groupthink, feedback

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1. Introduction

The study of Behavioral Operations is evolving into a recognized domain of research. This new field draws from multiple reference disciplines. Whenever intrepid researchers venture into new terrain, they find that they require knowledge outside of their formal training. For many, work in this area has meant a significant amount of time spent becoming familiar with the bodies of knowledge from other disciplines central to behavioral research.

A number of papers provide a useful introduction to the field. Bearden and Rapoport (2005), for example, focus on sequential decision making problems in OM and examine how people make these types of decisions compared with normative theory. The results they summarize are drawn primarily from controlled experiments. The paper also provides insights into how experimental data can be analyzed to test its deviation from normative theory, including the idea of identifying and testing decision heuristics that better match the data.

In contrast, Loch and Wu (2005) cover a broader spectrum of operations problems and provide guidance on how to incorporate more realistic behavioral attributes into analytical models. They examine behavioral issues due to individual decision making, social preferences, and culture.

Bendoly et al. (2006) review controlled experiments in Operations Management, describing the historical tendency for controlled experiments to be used in specific operations contexts as well as tendency for such studies to appear in certain scholarly outlets in contrast to others. These authors outline the rationale behind the use of controlled experimentation, several methodological best practices and examples of where critical gaps in our understanding of human behavior can be address by these approaches.

Gino and Pisano (2008) provide a general discussion and a blueprint for future research in the field, speculating on trends in recent research and conceptual connections between various areas of knowledge and theory that can be brought to bear in new research development.

In contrast to these works, this article discusses multiple areas of behavioral research and their potential contributions to OM. As a result, it is broader (but less deep) than previous work. The purpose of our article is to provide a 'jump start' for OM scholars interested in Behavioral Operations by describing theoretical foundations on which to develop new or extend existing plans of study. We identify some fundamental psychological, sociological and economic theories which research in Behavioral Operations can (and does) draw upon. It is not our objective here to provide a full review of these fields (each would take many books). Instead we highlight a few theoretical constructs and empirical phenomena which we believe are particularly informative for the OM community and have been helpful for us.

This article covers four main bodies of knowledge: cognitive psychology, social psychology, group dynamics and system dynamics, in each of four sections. The choice of these areas was based on an interest in touching upon various levels of examination and analysis under a more general rubric of 'judgment and decision making'. Distinctions among these bodies of knowledge can be summarized by characteristics and themes that may be typical of their application in the existing literature, as demonstrated in Table 1.

		Cognitive Psychology	Social Psychology	Group Dynamics	System Dynamics
Typical Unit of Analysis		Individual	Individual	Individual & Group	Group & Organization
Typical Methods	*Field Case Studies*	○	◔	○	◕
	Controlled Experiment	◕	●	●	◑
	Survey Methods	◔	◑	◕	○
	Math Modeling	◕	○	◔	◔
	Simulation	◔	◔	◔	●
Key Themes		Heuristics, Biases	Motivation / Goals, Feedback	Groupthink, Abilene Paradox	Stocks-and-flows, Delays

** For each body of knowledge, darker pies represent more predominant applications of methods.*
(Fully shaded pies represent "very common" methods, Empty pies represent "very rare" methods for the body)

Table 1: Summary of typical characteristics of 4 bodies of knowledge

As noted in the first row of Table 1, the typical unit of analysis in cognitive and social psychology are the individual, although both bodies of knowledge discuss the impacts of their findings on small groups and whole organizations. In group dynamics, the unit of analysis includes both the individual and the group. In contrast, studies in system dynamics focus on the group and organization level.

One of the difficulties researchers find when incorporating behavioral theory into their work is the wide range of research methods commonly found. Subsequent rows in Table 1 describe typical methods that these behavioral disciplines use. The first category, field case studies, refers to rich examinations of real-world settings through observation of actual practice, archival data and direct communication with those working in these environments. Controlled experiments are typified by multiple treatments and random assignment of participants to treatments, and include experiments conducted in real-world settings or constructed depictions of such settings, but are generally distinguished by the extent to which researchers control or manipulate features of these settings. Survey methods represent data acquisition from primary sources reporting on a range of both observable and tacit features of operational settings. Many of these surveys elicit retrospective perceptions. While controlled experiments and field case studies also often use survey techniques to supplement their main findings, this category refers to data which predominantly comes from surveys. Math modeling attempts to incorporate analytical representations of behavioral tendencies, utilities, or preferences into a decision framework that capitalizes on closed form, numerically generated or other related approaches to estimation. Finally, for comparison purposes, we designate 'simulations' as inclusive of computational simulation methods as well as evolutionary or dynamic simulation analyses.

The final row of Table 1 describes the main themes which will be covered in each of the subsequent sections. Each section provides two or three key *theoretical facets* from each field, and describes how these facets might affect or predict behavior in OM settings. We also provide guidance for where to go to learn more about each body of knowledge.

These bodies of knowledge and their associated theoretical facets can be applied to a wide array of OM settings. Each section describes a variety of applications and implications by way of illustration. In order to maintain a common theme to our discussion, as well as further emphasize the distinct theoretical values each body of knowledge contributes, the final subsection of each section discusses the impact of the theoretical facets on a unified OM setting: a retail grocery store with multiple service queues.

This particular setting was chosen in light of both traditional and continued contemporary interest in the relevance of human response and behavior in queuing systems (eg. Glazer 1958; Maister 1985; Larsen 1987; Seawright and Sampson 2007). More recent studies of human perceptions and behavior in service queues have focused on incorporating human attributes into customer satisfaction metrics (Chambers and Kouvelis 2006; Whitt 1999; Carmen et al. 1995). Still more recently, Seawright and Sampson (2007) studied 'observer responses' to queue dynamics in an attempt to assess wait-perception biases which might ostensibly impact near-term and future patronage rates. This area remains a rich domain for further study along these lines. We hope that the theoretical facets we identify will advance the literature in this context. More generally, we also hope that by providing a unifying example we can illustrate concrete ways that these bodies of knowledge can inform OM research regardless of context. Our overall goal is to lower the setup costs for new researchers in Behavioral Operations.

2. Cognitive Psychology in Operations

A large body of literature in judgment and decision making and behavioral economics concerns individual decisions. Of most interest for research in Behavioral Operations are domains where individual decisions deviate systematically, for a large portion of the representative population, from those decisions otherwise predicted by normative theory.

Systematic deviations are generally divided into two classes: *heuristics* and *biases*. A *bias* is an observed systematic deviation in decision-making, while a *heuristic* is a rule-of-thumb which people use to make decisions. Thus a bias primarily describes deviations in outcomes of decisions (e.g. not searching enough in the context of a secretary search task) while a heuristic primarily describes deviations in processes of making decisions (e.g. stop search once you identify an individual with quality in the top 20% of the distribution, regardless of the other factors). Note that heuristics can cause biases, as in this example, but not all heuristics and biases stand in this relationship to one another.

Heuristics and biases are identified using multiple methods. Many involve psychological and often incentivized (i.e., pay for attentive participation / performance) experiments in which respondents are asked for their judgments, choices or estimates in different treatments and the responses compared. A few involve surveys which collect data from a broader variety of the population. Math models also have been used to test how proposed heuristics and biases change decision outcomes by incorporating these assumptions into established analytical models. This approach takes the heuristics and biases as a given and focuses on their impact in various settings (e.g., Odean 1998 provides examples for behavioral finance).

The list of heuristics and biases is large, and indeed many books have been written describing them (see Plous, 1993 or Baron, 1998 for introductory texts). Here we identify three which have proven to be robust in a wide variety of settings, and which have immediate and important implications for OM problems. As mentioned in the introduction, these should not be considered a comprehensive list, but instead more of an existence proof of how these factors can be integrated into OM research.

2.1 Theoretical Facet 1: Overconfidence

Prior research suggests that individuals exhibit overconfidence in a wide range of applications (Muller 2007 provides an extensive review). Unfortunately, this literature has often confused a number of behavioral regularities under the rubric of 'overconfidence' (Healy and Moore, 2007 provide a nice review and characterization of this research). The traditional (pure) overconfidence bias is that individuals believe they know more than they do. In particular, they believe that their information is more precise (i.e., accurate within a tighter confidence level) than it is. Healy and Moore (2007) refer to this bias as *overprecision*.

Overprecision has important impacts on a number of OM areas. For example, consider a forecasting task. Typical OM models assume that individuals forecast optimally. Errors in forecasting are often attributed to misperceptions of demand distributions (e.g., perceptions of tighter ranges of potential demand, as might be associated with truncations of these distributions). These are errors in overpercision. Accordingly, an overprecise forecaster will under-estimate the variance of the value they are forecasting, leading to systematic and predictable errors in decision-making based on those forecasts. In secretary search problems, overprecise decision makers might search too little, assuming that the variance of the distribution they face is smaller than it really is. In inventory problems, overprecision might cause individuals to hold too little safety stock, as they under-estimate the variance of demand or variance of lead-time, which they are likely to face. Some current research analytically investigates the impact of overprecision in the newsvendor model (Croson, Croson and Ren, 2008). This model shows that overprecision on the part of newsvendors leads to under-ordering when the ratio of price to costs is high (high-margin goods) and over-ordering when the ratio of price to costs is low (low-margin goods), relative to optimal orders. Interestingly enough, this is exactly the pattern which has been observed in experiments on newsvendor orders (Schweitzer and Cachon 2000, Bolton and Katok 2004; Benzion et al. 2007).

An alternate type of overconfidence relates to the *overestimation* of one's own abilities in a particular domain (Healy and Moore 2007). Overestimation has been used extensively to predict entrepreneurial activity and entry, R&D expenditures, and other business decisions (e.g. Camerer and Lovallo 1999). In the OM context, overestimation might lead to excessive investment in (new) product development, systematic under-estimation of cycle time, error rate, or other negative performance attribute. It can also lead to overoptimistic estimates of demand, time-to-completion of projects, delivered service levels, customer retention (for a given service level), and may bias decisions in many other settings.

2.2 Theoretical Facet 2: Anchoring and Insufficient Adjustment

A second behavioral regularity involves how individuals estimate facts which they do not know. A large body of experimental work suggests that estimates are influenced by environmental or situational factors which, in theory, should not matter. In particular experiments repeatedly demonstrate that individuals anchor their decisions or responses unduly on otherwise irrelevant past observations and experiences (Bowman 1963). Adjustments of these anchored estimates to the current context are typically insufficient (Tversky and Kahneman 1974).

Like overprecision and overestimation, anchoring is likely to have a direct impact on forecasting activities. If individuals making forecasts are susceptible to anchoring, then unrelated but mentally available factors will influence their forecasts. One available factor which is often used as an anchor is that of previous draws from iid distributions; this leads to biases like the hot hand (where individuals believe that iid sequences are positively autocorrelated). In OM, this would translate into forecasts of demand which are closer to the previous period's demand than they should be.

In inventory management, Sterman (1989a) proposes an anchoring and adjustment heuristic as a possible explanation for observed ordering behavior in the Beer Distribution Game. He finds that the anchoring and adjustment heuristic captures participants' ordering decisions and leads to systematic biases. In particular, in placing their orders participants insufficiently account for the supply line of orders placed but not yet received, generating overordering and supply chain instability.

Similarly, managers may anchor on the previous success (or failure) of new products in determining whether to develop and introduce yet another product. They may anchor on previous realizations of demand when determining next period's ordering or inventory decision. The trick with using anchoring models for prediction and explanation is that one needs to know *what the anchor is* which influences the decision at hand. Anchors are abundant in the field, and an anchor can be found which is consistent with (almost) any mistaken decision. Researchers attempting to apply this heuristic to OM decisions need to decide *ex ante* what the anchor is likely to be, and generate testable predictions on that basis.

2.3 Theoretical Facet 3: Loss Aversion, the Reflection Effect and Framing

A number of papers have independently identified the reoccurring tendency for individuals to treat losses asymmetrically from gains. Research has identified two types of asymmetries between losses and gains. The first, termed *loss aversion*, suggests that the subjective value of losing is, in absolute value terms, greater than the subjective value of winning. Thus losing a fixed amount hurts more than winning that amount feels good. The second asymmetry, termed the *reflection effect*, suggests that individuals are risk-averse in gains, but risk-seeking in losses. Thus risk attitudes depend on whether individuals are facing a gamble which involves winning or losing money. Both these regularities are analytically modeled in *Prospect Theory* (Kahneman and Tversky 1979). *Framing* (discussed at the end of this section) describes how individuals decide whether they are facing a loss or a gain. Adjusted utility functions have also rather recently been used in analytical models in the operations literature to capture these regularities (cf. Tomlin and Wang 2008; Tamura 2007).

Loss aversion suggests that individuals experience losses and gains differently. For example, imagine a manager setting targets for the upcoming year. We usually model a target-setting rule which involves equal penalties for overachievement and underachievement. However, if the manager anticipates that missing the targets (losing) will be twice as painful as making the targets (winning), then (s)he will be tempted to set targets that are significantly too low. Similarly, in new product settings, abandoning (losing) an existing market, even one which is unprofitable, might be perceived as more painful than acquiring a new market is beneficial. This might lead firms to invest too many resources in holding onto unprofitable products or markets, and under-invest in new product development or R&D.

The second regularity, the reflection effect, is a further refinement to risk preferences. Experiments demonstrate that individuals are risk-averse in the domain of gains. For example, they prefer $50 for sure to a 50-50 gamble between $0 and $100. However, they are risk-loving in the loss domain. For example, they prefer a 50-50 gamble between $0 and -$100 to losing $50 for sure (Kahneman and Tversky 1979). This regularity suggests, unlike typical expected utility theory, that one cannot model decision makers with one risk parameter (e.g. CARA or CRRA utility functions; cf. Levine and Zame (2002), Balvers and Mitchell (1997)). Similarly, it suggests that managers may be too risk-averse in policies which may involve gains, and too risk-seeking in policies which may involve losses. This can lead to *escalation of commitment* to new product development initiatives which are losing money (or new product introduction, or IT investments, or other settings; see, e.g. Khuval et al. 2008). Managers have already taken losses on the initial attempts, and they now become risk-loving, continuing to invest resources in an attempt to get themselves back to even.

Finally, both these biases suggest that managers may be susceptible to *framing* (Tversky and Kahneman 1981; Amaral and Tsay 2009). That is, the way that the problem is described can influence the decision that they make. In the classic framing experiment, individuals choose between two vaccines for a rare Asian disease, expected to kill 600 people. Two alternative programs to combat the disease have been proposed.

Program A: 200 people will be saved

Program B: there is a one-third probability that 600 people will be saved, and a two-thirds probability that no people will be saved

72 percent of participants preferred program A, the risk-averse choice. Note that these policies are described (framed) in terms of gains (people saved). Thus individuals are risk-averse, choosing the sure thing over the gamble with the same expected value.

A second group of participants choose between

Program C: 400 people will die

Program D: there is a one-third probability that nobody will die, and a two-third probability that 600 people will die

Now, 78% preferred program D, the risky choice. These policies are described (framed) in terms of losses (people dying). Thus individuals are risk-loving in losses, choosing the gamble over the sure thing. Here the gambles being faced are identical, simply *described* differently.

This framing bias also has important implications for operations managers. The way that choices are described can influence decisions made about inventory policies, investments in IT software, new product development, and in many other settings. However, the nuances involved in the exact wording and situations which trigger framing effects make it a difficult tool to use precisely (Schultz et al., 2008).

That said, framing also offers an opportunity for debiasing of loss aversion and the reflection effect. When a manager is considering a decision which involves gains or losses, (s)he can also consider the same decision in the other domain. For example, consider the decision to invest in a new inventory tracking system. The manager is deciding whether to invest $500,000 in order to, with some probability (say 95%), save $600,000 in the future. Loss aversion might play a role here, and the loss of $500,000 might loom larger than the potential future savings of $600,000. Instead the manager can reframe the problem in terms of the company's (or the division's) net worth (imagine this is 5 million). Now the choice (s)he is facing is an 95% chance of 5.6 million versus a 5% chance of 4.5 million as compared with 5 million for sure. This gamble, all in terms of gains, might seem more attractive than the one which involves a loss of the initial investment. Thus by re-framing the decision, the manager can be induced to make the profit-maximizing move.

2.4 Putting it together: Cognitive Psychology

Let us consider how these theoretical facets might impact behavior in the grocery store example alluded to earlier. If the store employees *overestimate* their accuracy and speed (their abilities), they might not check (or catch) mistakes in ringing up customers, especially for non-automated tasks like inputting produce codes. These instances of overconfidence will introduce errors into the checkout process. These errors might in turn cause inventory and subsequent ordering errors, for example when POS data is used for re-ordering (e.g. ordering more tomatoes instead of apples, when the cashier uses the wrong produce code).

If the customers suffer from *anchoring and insufficient adjustment*, they might systematically make errors about which queue they choose to join. For example, shoppers might *anchor* on the number of people ahead of them in line, then *insufficiently adjust* for the size of their orders (the number of items in the grocery cart). This will lead to longer and uneven wait times. If managers suffer from *anchoring and insufficient adjustment,* they might mis-estimate the number of customers who will need service, thinking it will be closer to demand on previous days and only insufficiently adjusting for idiosyncratic factors like sales, holidays, or the state of the economy. These errors can lead to mistakes in ordering of inventory, or under (or over) staffing of registers or customer service personnel.

Finally, *framing* can affect customer decisions. European-style policies in which customers pay, even a nominal fee, for the shopping bags they use, can both induce customers to bring their own bags but also can decrease the amount of their purchases or even induce them to choose a different store. Paying for something that used to be free is often perceived as a loss. In contrast, offering a discount if customers bring their own bags is perceived as a gain, and can have positive effects on customer loyalty and green initiatives.

How could the existence of such impacts, and theoretical linkages to the discussed behavioral phenomena, be tested or incorporated into larger studies of operations? Methods such as field-based action studies, where real-world organizations permit investigators to manipulate work conditions and observe associated operational effects, could certainly be informative empirically. In a grocery store setting for example, this would involve working with management to put into place alternative service policies, observe their operational effectiveness and poll both individual customers and workers on their perceptions of these alternative policy settings. Alternately lab experiments (involving artificial grocery settings and perhaps even individuals who are not presently employed in the grocery industry) can also prove helpful in enriching our understanding of such phenomena and their potential impact. Ultimately, once observable behavior can be operationalized such normative models of behavior hold great potential for integration with more traditional analytical models used in studying the specific operational context.

In summary, OM models and empirical research typically assume that individual actors are perfectly rational with unlimited reasoning abilities. In contrast, a large body of literature demonstrates that individuals are boundedly rational, use heuristics for decision-making and suffer from systematic biases. An understanding of, and integration of, these regularities into OM models and empirical research has the potential to improve our predictive power and deepen our understanding of OM systems and behavior.

3. Social Psychology in Operations

While heuristics and biases are likely to impact decision making and associated actions, the choices people make are also influenced by their motivation. Motivation affects conscious and unconscious decisions pertaining to effort, persistence and planning. Motivation, in turn, is influenced by the goals people hold, the feedback they receive and the way they interact with the people around them. These features: goals, feedback and interdependence are affected by the way work is organized. Operations models often depend on or suggest changes to the way work is organized without considering the impacts on motivation and subsequent decisions. This leads to both direct and indirect effects that cause discrepancies between model predictions and outcomes.

Industrial and oganizational (IO) psychology studies how changes to the technical system can affect the motivation of individuals. Boudreau et al. (2003) point out that most operations models assume that the behavior of individuals is independent of the decision parameters of the model. For example, most models of production lines assume that worker speed is independent of the size of the buffers. Schultz et al. (1998) show how this can lead to models that under-predict productivity in low inventory lines.

Since goals, feedback and interdependence affect human motivation there is virtually no area of OM research to which they can not apply. Inventory models assume different stockout measures and different review policies which involve different goals and feedback. Line design and queuing are affected by interdependence among workers, servers or customers. Project Management is greatly dependent on feedback. Procurement and strategic sourcing is concerned with building interdependent relationships among actors.

A wide range of theories in IO Psychology are useful in considering the motivational effects of operations decisions. The Handbook of Industrial Work and Organizational Psychology (2001) or the Handbook of Industrial and Organizational Psychology (1992) each give overviews for many pertinent theories. Here we will highlight a few of the more established lines of theory: Goal-Setting, feedback and Control Theory and interdependence. Most theories in IO Psychology are built upon observation and tested in experiments using human subjects. Experiments are used in order to tightly control the variables under study and are usually devoid of any context relating directly to OM problems. They are generally considered to test a general theory of human behavior which, theoretically, could then be applied in any particular context. This in itself provides a rich opportunity for OM researchers to draw on this body of knowledge for future context specific research in Behavioral Operations.

3.1 Theoretical Facet 1: Goal Setting Theory

The performance goals that individuals have for a particular task have a profound effect on how well they perform those tasks (Latham and Locke, 1991). The research on Goal Setting Theory is extensive and conclusive, and is one of the more robust and generally accepted theories in IO Psychology (Kanfer, 1990).

The properties of the goal and characteristics of the work setting are important to the effects of goals on performance. Goals of the type 'do your best' do not generally lead to enhanced performance. Difficult, specific and measurable goals, where the agent appreciably affects the outcome, lead to higher performance than easy or non-specific goals. Effective goals lead to higher levels of effort, increased persistence as well as higher levels of strategic planning and increases in learning. In order for goals to have maximum effect, the individuals must be committed to the goals, relevant feedback must be available and individuals must have the skill, knowledge and ability to perform the task (Donovan et al., 2001).

There are situations where the goal of short term profit maximization is not the most appropriate long term goal. Evolution has taught humans that social considerations are important to long term success. People will forgo short term monetary gain for social reasons believing, consciously or unconsciously, that they will be better off in the long run. These behaviors persist even when the benefits of social ties are ill-defined and uncertain. Business-to-business marketers have long known that relationships often count as much as price. Price may qualify you to compete for business, but it is the relationship between the salesman and the decision maker that often proves crucial. This is in part because so much of the buyer-supplier interaction has to do with things that are not contractable. Many of us, when we have a broken automobile for example, will eschew the cheapest mechanic for the one we can trust and will continue to return to that mechanic without doing optimization searches each time we have car trouble. That mechanic knows that he wins in the marketplace by setting and achieving goals that include relationship building.

Operations models tend to outline specific objectives however they usually do not select those goals with much thought to their effects on motivation. Inventory models often account for the costs of running out of stock either through cycle fill rates or lost sales. We know of no studies that have considered any possible motivational consequences of these metrics. Perhaps models using cycle fill rates may be superior in their motivational power even when they are an inferior fit with the actual cost structure.

There remains a general lack of understanding regarding human motivational mechanisms as they relate to operational objectives in a variety of contexts.

The alignment of individual goals and organizational-level goals assumed in developing operational policy are clearly critical. Doerr et al (1996) find a difference of 25% in productivity on a fish packing plant when goals are properly matched to the flow policy of the line. Linderman et al (2003) further emphasize how goal specification in six sigma projects can promote alignment and drive performance. In contrast Sevier (1992) notes that a lack of clear, specific and attainable goals can cause JIT implementation projects to fail. Chen, Lin and Thomas (2003) show that models assuming a fill rate goal in an infinite time horizon (hence largely ignoring human motivational issues) will overstock items under a limited time horizon contract. Correcting for the potential advent of such failures requires increased understanding of how individuals are motivated in these settings and how these motivations can either be better aligned with operating objectives or how operating objective might be augmented.

Operations models can contribute to setting appropriate goals. For example, models of M/G/s steady state queue length are useful in understanding line relationships. This leads to the development of intermediate goals, changes in capacity utilization or variability for instance, that can be implemented at the individual level and which enable the achievement of higher level goals like profit maximization. Mathematical models provide the understanding of the system that allows for setting appropriate goals. On the other hand, choosing objective functions that lead to clear, meaningful, measureable and actionable goals, will lead to better implementation.

3.2 Theoretical Facet 2: Feedback and Control Theory

The central theme of Control Theory models of motivation is that individuals use feedback to look for differences between their goals and their performance in order to regulate their behavior (see also Campion and Lord 1982 and Bandura 1991). Donovan (2001) writes:

> "Individuals monitor their behavioral outputs through an environmental sensor that allows them to make comparisons between their current behavior and their behavioral referent (i.e., their goal or standard). If this comparison does not detect any goal-behavior discrepancies, the individual simply maintains their current behavior(s)." (p 64.)

Since people use feedback to monitor the results of their behavior and make adjustments, the salience, timeliness and relevance of the feedback they receive is critical. Systems which provide no feedback towards goal accomplishment will be ineffective. For example, if ordering costs cannot be measured, then a goal of equating ordering and holding costs will be difficult to implement. If the extent of inventory shortages is unknown, a goal to reduce them is unlikely to motivate action.

Feedback affects the productivity of production lines. Much of the Toyota Production System is about making discrepancies obvious (e.g., Create continuous process flow to bring problems to the surface; Use visual control so no problems are hidden; Grow leaders who thoroughly understand the work; Become a learning organization through relentless reflection (Hansei) and continuous improvement (Kaizen)). Sewell and Wilkinson (1992) observe how JIT systems increase the ability of workers and managers to observe work rates. This increases feedback showing differences between the goal and attainment and explains part of the success of the Toyota Production System in practice. Brown and Mitchell (1991) discuss improvement in the use of work information with JIT. Schultz, McClain and Thomas (2003), in a behavioral experiment, show that feedback changes worker processing times from high to low inventory lines. Huber and Brown (1991) discuss improvements in feedback when changing from batch production to cellular manufacturing. Schultz, Schoenherr and

Nembhard (2009) use archival data to demonstrate that workers react to the pace of work around them.

Models with decision variables which do not account for the frequency and availability of feedback will have motivational consequences that can significantly and negatively impact the outcomes. Katok, Thomas and Davis (2008) show that feedback frequency can have important consequences for service level agreements in inventory contracts. Placing the decision maker close to the source of the feedback can improve the timeliness of the feedback and hence the motivation. For instance, centralizing inventory decisions to reduce demand variability may have unintended consequences if it also reduces customer feedback. Goal attainment would be improved if the person ordering the inventory comes into physical contact with the results of his or her decision.

Feedback also has important consequences for quality control. Juran (1995) talks about the importance of the feedback cycle to quality control and the benefits of self inspection. Stewart and Grout (2001) also show how many of the benefits of mistake proofing involves improved feedback.

This does not mean any increase in the level of feedback to ensure timely, high quality and salient information should be seen as a singular objective. Certainly there are penalties to overwhelming individuals with information. RFID mechanisms can greatly increase the amount and accuracy of feedback, but they may not lead to better decisions. Bolton and Katok (2008) show that longer period feedback which aggregates variability leads to increased learning in inventory ordering problems. The salience of competing feedback can also motivate unwanted behavior. The most salient feedback will often get the most attention. If the goal is to move the car, and noise acts as feedback, then the squeaky wheel will get the oil. More important goals may suffer as individuals pay attention to less important but more salient feedback. Since many operations decisions involve tradeoffs, systems which increase the salience of feedback on one of the tradeoffs, but not the others, can lead to motivational inconsistencies. The selection of the most appropriate forms of feedback must be pursued cautiously and intelligently in order for the benefits of an effective feedback system to be realized.

Operations models are quite good at helping us understand the relationships between elements in a process. At the same time, these models offer a great opportunity for future behavioral augmentation. For example, future models and systems could be designed with a consideration of the feedback consequences. As a benchmark, some recent work does already exist in which human responses to changing model states are incorporated in their analysis. Powell and Schultz (2004) model a production line where worker processing times are a function of the state of the buffers. Filliger and Hongler (2005) also present a queuing system analysis of production flow lines with buffer dependent work rates.

3.3 Theoretical Facet 3: Interdependence

The interdependence of workers has a profound and often complicated effect on motivation. Interdependence in work situations can be divided into *outcome* interdependence and *task* interdependence. Wageman and Baker (1997) define outcome interdependence as "the extent to which the rewards that accrue to an individual depend upon the performance of coworkers," and task interdependence as the "degree to which an individual's task performance depends on the efforts or skills of others." (For more on classifications of interdependence see Steiner 1972).

Outcome interdependence (joint rewards) can lead to free-riding, or to the development of norms (Olson, 1965). In free riding, individuals realize that they do not enjoy the full benefits of their efforts; those benefits are shared among their co-workers. This induces them to exert less effort than would be optimal (or than they would if there were no outcome interdependence). This effect is also documented in Social Loafing Theory (Williams et al., 1981). On the other hand, reward interdependence can also lead to workers having a stake in the effort of others and can lead to higher efforts via peer pressure (Kendal and Lazeur, 1992). Which of these effects will dominate depends on the situation, the individual motivation, and the setting. One regularity from these theories is that the effectiveness of motivation under outcome interdependence depends on how well efforts or contributions can be identified with the individual.

For example, Schultz et al. (1999) found that reward interdependence encourages the development of productivity norms in work groups. Productivity norms will not necessarily lead to an increase in motivation. Rather they will lead to diminishing the variability around the mean among group members. A particular level of effort or output is determined to be appropriate and is enforced by peer pressure from the group. It is hard to predict whether the development of productivity norms will increase or decrease output but they will lead to a decrease in variability among workers.

Kerr et al. (2007) have looked at the effects of different types of task interdependence on motivation. The Kohler effect postulates that poor performers will increase effort with congruent tasks like serial production lines. The results with additive tasks, like parallel processes, are mixed. However an analysis of archival data by Schultz et al. (2009) show workers adjust their work speed toward the average speed of the group in parallel tasks.

Doerr et al. (2002) propose a model of how task interdependence confounds effects of worker heterogeneity on work line design. They look at both dynamic and static rules for task boundaries. Dynamic boundaries involve types of Worksharing (McClain, Schultz and Thomas, 2000), including Bucket Brigades (Bartholdi and Eisenstein, 1996), U-Shaped Lines (Zavadlav, McClain and Thomas, 1996) and Dynamic

Line Balancing (McClain, Thomas and Sox, 1992). These are systems of worker flexibility where tasks on any particular item are dynamically assigned to reduce the effects of variability. These systems, which increase interdependence, have been shown to have positive effects on productivity.

Changing the way people relate to each other through their work can have profound effects on their motivation in very complicated ways. Models which inherently include changes to these relationships might be considered more carefully. One line of research for example might involve a consideration of what effects changes to work relationships will have on desired outcomes. Some unique findings may emerge from such inquiry, as demonstrated by Siemsen, Balasubramania and Roth's (2007) work on the role of incentive mix in contexts subject to various interdependencies.

3.4 Putting it together: Social Psychology

To illustrate some of the questions involved, consider the decision to consolidate lines in the grocery store setting with multiple checkout lines. Basic queuing theory tells us, generally, that consolidating the line may lead to reduced inter-arrival variability and decreased waiting time. Therefore multi-server, single line systems should perform better than multi-server multi-line systems.

This research usually assumes a goal of shorter waiting times as a proxy for customer satisfaction. However, work in the marketing literature shows that the link between waiting time and satisfaction is complex and not fully understood (Baker and Cameron, 1996). Some work has been done to integrate the psychological and mathematical literature (Carmon, Shanthikumar and Carmon 1995 for instance), however much remains to be done (Bitran, Ferrer, and Oliverira, 2008)

The single or multiple line decision also has effects on feedback, both to the customers and to the servers. Multiple queues are closer and therefore more salient to the servers. They put the customers closer to a particular server and change the time and variability between state changes in the system. We do not currently know how these differences in feedback affect either the servers or the customers.

Changing the line from multiple to single queues also changes the dynamics of interdependence among the servers, and between the servers and the customers. Single queues increase the reality, and even more the perception, of interdependence among the servers. What one server does now has direct implications for the other servers. Servers will naturally find themselves more interested in the serving rates of others. Customers in line no longer have a one-to-one relationship with servers. The interdependence relationships have changed between the customers and the servers. Will servers' motivation to work quickly and accurately be changed by a lessening of this one-to-one relationship?

In summary, OM models often ignore the impact of design parameters on motivation. Researchers can integrate theories and findings from goal-setting, feedback and interdependence in order to enhance the models' predictive and explanatory power, and in order to design more effective operational and motivational systems. For those interested in more insights into this body of knowledge for use in their own efforts, we again refer them to key resources on theory such as The Handbook of Industrial Work and Organizational Psychology (2001) or the Handbook of Industrial and Organizational Psychology (1992).

4. Group Dynamics in Operations

The prior sections focus on the impacts of individual psychology in Behavioral Operations; either how individual decisions may be biased or how goals and incentives might influence individual behavior. Additional twists to these stories develop from the group dynamics literature, particularly when the work environment involves both task and outcome interdependence. This body of knowledge investigates how individuals perceive themselves as members of a collective, and how they jointly (rather than individually) confront decisions.

Common OM application contexts in which group dynamics are most salient include project management, cellular manufacturing, quality circles, and new process and technology implementation. However generally speaking, any operational context involving interpersonal interactions and/or performance interdependence may be subject to group dynamics. Common methods used for data collection in researching these contexts include field observation, archival methods, survey, and controlled behavioral experiments. Analytical methods include a wide array of standard statistical model fitting approaches (eg. linear regression, time series, SEM, etc.) as well as simulation and social network analysis.

In this section we examine three group dynamics issues which could be incorporated into OM models: Groupthink/Abilene Paradox, blame, and breakdown Spirals. Comprehensive reviews of some of the past research on these related topics can be found in Esser 1998 and Mullen et al. 1994. For more recent OM applications and discussions of the dynamics of these phenomena see the works of de Treville and Antonakis (2006); Bendoly and Swink (2007); Bendoly and Cotteleer (2008).

4.1 Theoretical Facet 1: Groupthink and the Abilene Paradox

Janis (1982) originally described groupthink (GT) as a "mode of thinking that people engage in when they are deeply involved in a cohesive group, when the members striving for unanimity override their motivation to realistically appraise alternative courses of action" (p. 9). GT causes a shift in what individuals want; even if at the beginning of the group interaction they had different ideas, by the end their preferences reflect the consensus of the group. While hasty and potentially irrational consensus-making is typically attributed to GT, in recent years authors have attempted to distinguish the behavioral mechanisms associated with GT from another undesirable group decision-making phenomena referred to as the *Abilene Paradox* (AP).

Harvey (1974) originally described AP as instances when group members, and hence groups as a whole "frequently take actions in contradiction to what they really want to do" (p. 18). In GT individuals' goals change to reflect the desire to conform to the group. In AP in contrast, individuals' goals don't change, but their decisions still reflect the groups' decisions. Thus the individual experiences dissonance and tension. These distinctions between GT and AP may appear subtle, but have real implications in work environments (Kim 2001; and Taras 1991).

For example groups driven by the AP and making new work-sharing decisions are unlikely to follow these decisions themselves, and are in fact likely to act in ways that undermine the very policy they derived. One such action may involve attempting to revert to prior individual modes of activity by seeking out ways to discretely circumvent policies newly put into place. This might involve falsifying claims of procedures followed, which in turn could actually lead to deliberate accounting errors that might leave no indications of manipulation and hence prove difficult to interpret after the fact. In contrast those making (even obviously poor) decisions under GT (e.g. severely cutting off strategic investments in R&D to generate short term cost reductions) are likely to remain irrationally supportive of these decisions, continue to defend them longer than otherwise would be natural, and be more likely to reject reasonable corrections. Unfortunately, with no motivation to even account for the existence of reasonable alternative courses of action these GT dominated contexts face a great deal of potential lost opportunity for knowledge gains that could otherwise advance operating practice. It would indeed be interesting to reconsider accounting records for the occurrence of anomalies and cross check these with retrospective interviews and assessments of group dynamics to test empirically whether GT- or AP-like phenomena might be at play.

Both GT and AP cause groups to make suboptimal decisions. Both are caused by pressures on group members, often due to situational constraints (e.g. insufficient time, training or resources) of the operational work environment. For example, excessive peer pressure is an oft-cited cause of GT. External pressures stemming from the organizational structure, for example floor supervisors that chart performance of an assembly line group, or COOs that pass judgment on the effectiveness of a purchasing group, can also contribute to GT. These external pressures threaten the general welfare of the group and its members, increase group solidarity and hence GT behavior. Here again research approaches that tie empirical accounts of constraints to empirical accounts of activity, coupled with individual and assessments of group dynamics could prove an interesting route for investigation. The inclusion of such potential linkages into comprehensive mathematical models in an attempt to anticipate the complex interplay between situational constraints and performance, in the presence of one type of group dynamic or another, could be highly informative.

It is important to note that it is possible for both AP and GT to exist simultaneously, since groups may transcend multiple operational settings. Most people have experienced group contexts in which both external pressures on the group and pressures that restrict individual voice exist simultaneously. In OM, project management contexts are ripe for these sort of phenomena (Bendoly and Hur 2007). In such settings the conclusion of group work may be exalted with cheers of "We DID it…wow!" (e.g. we completed an implementation project on time, meeting all current operational needs) while simultaneously and paradoxically greeted with a sense of impending doom and discontentment “We did IT… ugh!” (e.g. recognizing that each individual’s personal perspectives of risk regarding future system capability deficits have not fully been addressed).

In AP, even after a group has made a decision, individuals may be privately committed to their own views, and hence suffer pain, frustration, irritation, anger or feelings of incompetence (Kim 2001). This unresolved dissonance can linger and may be expressed later through passive resistance toward implementing group decisions. Bendoly and Cotteleer (2008) illustrate just such a mechanism at play in an ERP implementation context. Managers describe passive resistance to technology-driven process changes, and eventually active workarounds as they gained familiarity with the system (in some cases months after ‘go-live’). Similar active undermining of newly imposed processes arrived at through AP-prone groups are demonstrated by controlled experiments.

Overall the negative implications of poor group decisions, influenced by GT or AP or both, are rampant. For example, groups subject to GT can implement new quality control policies that do more to complicate work than to allow for easy identification of bottlenecks and failure points. Groups subject to AP can generate new product designs which fail to incorporate a host of distinct integration capabilities necessary for mid-term market adaptability (even if these capabilities had been individually considered crucial by various members of the design group). As already suggested, these delayed effects can prove to be the most insidious for operations managers yet are seldom a focal point in traditional operations management research.

4.2 Theoretical Fact 2: Blame in Groups

Workplace problems, relating to GT/AP or otherwise, are inevitably associated with workplace blame. But blame tends to be subject to errors in perceived causation (attribution errors), which create operational and organizational difficulties. In this section we discuss how group members assign responsibility for outcomes, and how these assignments may impact behavior.

Attribution Theory suggests a tendency for individuals to ascribe poor outcomes to others (either their traits or their actions), rather than to themselves or the situation (Bendoly and Swink 2007; Taylor and Fiske 1975; Heider 1958). For example, in Weber et al.'s (2001) study of coordination games, individuals blamed others for poor outcomes, instead of features of the situation like group size, complexity or other barriers to performance. Similarly in the Beer Distribution Game participants blame others (either other players or the game coordinator) for poor performance, rather than the structure of the system generating the instability (Sterman 1989a). This error prevents individuals from identifying the need for changes to operational systems for performance improvement.

Attribution theory also predicts when and which attribution errors will be observed in the presence of GT and AP. Decisions motivated by GT tend to be associated with external pressures, thus poor outcomes are likely to be attributed to these external pressures (i.e. it was the external-manager's/outgroup-member's fault this happened). This attribution increases the cohesiveness of the group, hence increasing the likelihood of further GT processes. In contrast, poor decisions motivated by AP are often characterized by situations in which no one is willing to take ownership of the process or outcome (Kim 2001). Thus poor decisions are more likely to be attributed to individuals within the group, leading to additional group fragmentation. This doesn't necessarily mean the dissolution of a group but rather an increasingly fractured interaction.

Attribution and blame errors have important implications for operations settings. Work sharing programs, assembly line settings and group project work often assume a willingness to accept responsibilities handed off by peers. Attribution errors (the likelihood that you will be blamed for poor outcomes) can impede rational motivations to engage in these programs. Blame also leads to mistrust, non-willingness to share (information or physical resources), an altered sense of accountability, greater distortions in estimation and weaker adjustment mechanisms, to name a few (Bendoly and Swink 2007). If blame is serious and endemic element of an organizational environment, its effects can be pervasive across multiple operational activities and can be informative in predicting the effectiveness of a given work-structure.

4.3 Theoretical Facet 3: Breakdown Spirals in Group-Work

These two factors (GT/AP and Blame) can cause breakdown spirals in group work. A conceptual map of these forces is shown in Figure 1.

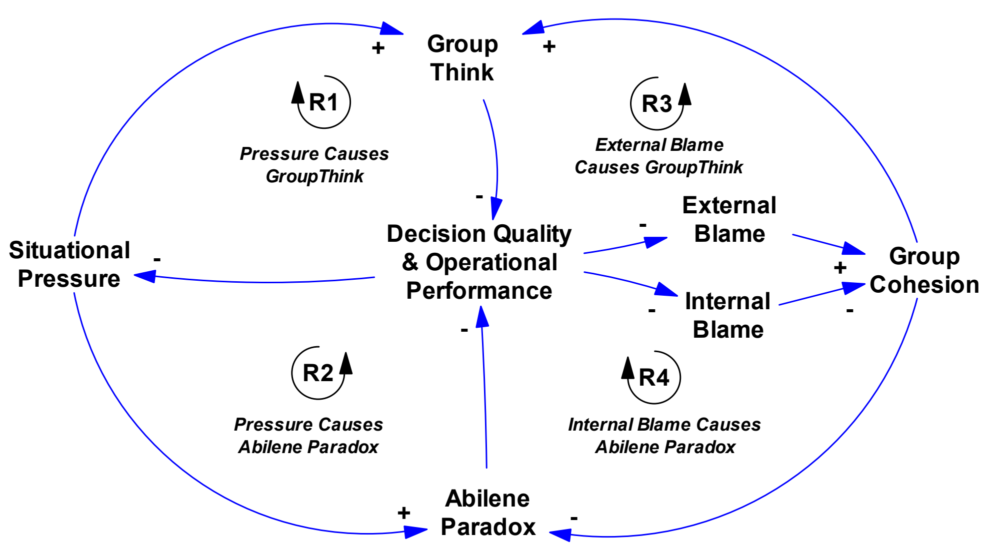

Figure 1. Pressure, blame and performance surrounding group dynamics

Note: Arrows capture the flow of information and the direction of causality. Signs ('+' or '–') at the arrowheads indicate the polarity of the causal relationships: a '+' means that, all else equal, an increase in the independent variable causes the dependent variable to increase (a decrease causes a decrease); analogously, a '–' indicates that, all else equal, an increase in the independent variable causes the dependent variable to decrease (a decrease causes an increase). The loop identifier (R1) indicates a reinforcing (positive) loop. See Sterman (2000) for further details.

As a prelude to the system dynamics section below, it is worth noting the feedback loops in this causal map. Poor performance leads to increased situational pressure causing both GT and AP. In addition, poor performance results in blame (internal or external) which subsequently intensifies group cohesion or fracture, and which further exacerbate the GT and AP. This can cause a breakdown spiral, where the decisions which groups make become increasingly worse over time.

For example, programs with quality control, monitoring and accounting systems may penalize group members for failure to meet performance requirements, providing situational pressure. Poor outcomes (missed quality control thresholds, for example), create the need for group members to attribute failure and thus blame others (internal or external to the group). Threats of further penalties increase pressure, reinforcing the poor decisions.

These systems create inefficiencies in social and operational structures in organizations and exacerbate the negative implications of both GT and AP phenomena (Chapman 2006). Even environments in which GT and AP are relatively marginal can evolve into highly charged and anti-productive work settings. For example, Bendoly and Cotelleer (2008) observed variance inflation in operating environments over time, caused by external blame. Individuals expressed their frustration by creating operational workarounds, resulting in the breakdown of standardization efforts.

These breakdown spirals pose threats to operational effectiveness. However group dynamics theories can guide the OM practitioner and researcher in predicting and avoiding them. Interventions to reduce GT often involve formal splitting of groups (at least temporarily), while interventions to reduce AP may require entirely new incentive structures for the individuals in the group, enabling and encouraging them to express their private opinion, even when it is different than that of the group (Kim 2001).

An alternative line of attack is suggested by the cross-cultural literature. Zemba et al. (2006) suggest that collectivist cultures are more likely to ascribe blame to group structure and dynamics than are individualist cultures. This suggests that the spiraling nature of AP and GT may be less of a threat in collectivist than in individualist cultures. As more companies engage in offshoring and outsourcing, and thus increase the use of teams with mixed cultural backgrounds, we may see a moderation of breakdown spirals. Studies of work settings in which groups produce or plan need to consider the implications of these dynamics and use them to inform models and develop prescriptions.

4.4 Putting it together: Group Dynamics

Several aspects of our grocery store setting are prone to the kinds of group dynamics phenomena discussed here. Consider for example the range of interdependencies among multiple agents in the checkout lines. One common activity is jockeying. The psychological determinants of even an isolated case of jockeying are far from adequately explored. Nevertheless the phenomenon has long been and continues to be incorporated in some form in mathematical models (cf. Blanc, 2009; Zhao and Grassmann, 1990; Koenigsberg, 1966; Glazer, 1958). Associated discussions, such as that provided by the classic work of Larson (1987), provide additional rich descriptions of some of the issues that can promote jockeying. For example the prospect of skipping (advancement ahead of those already queue; perhaps ahead of an individual) compounded by the fear of slippage (having others in a neighboring queue advance at a faster pace), can contribute strongly to an individual's decision to jockey. To complicate matters however, anyone who has ever been to a grocery store knows that a single incident of jockeying often is immediately accompanied by 'follow-ons'; i.e. individuals that see one person jockey and decide to follow a similar course of action.

Follow-ons reveal group dynamics in their most reactionary form. Group psychology, even in the absence of a formalized group structure, can lead individuals to blame either the cashier or the customer-in-service for a less than ideal pace of a line. If they find themselves advancing faster (skipping) in the line they've moved to this blame can be exacerbated (since this observation of pace change may further suggest inadequacy of the former cashier for example). Interestingly, if no improvement is found, individuals prone to GT may actually shift blame to the store or management in general (ie., to the general external forces that may be impeding the search for improvement) (Maister, 1985). If the blame to the store is strong enough, customers may suffer a confidence breakdown, preventing future patronization. Conversely, those customers prone to AP are more likely to blame those who may have begun the jockeying cascade that they jumped on board with. These individuals may 'dissolve' their ad-hoc group and even return to their original line. The breakdown in trust and confidence among fellow shoppers can discourage copycat jockeying in the future, even if it may otherwise be expeditious for both shoppers and the store.

Also interesting are the kinds of reactions that groups, based on either GT or AP dispositions, have to events such as individuals letting others into the line ahead of them (cutting allowances, as discussed recently by Oberholzer-Gee, 2006). In waiting lines populated by individuals prone to GT, perhaps supported by an established common feeling that the service firm is largely to blame for queue difficulties, reasonable allowances for cutting may be easily accepted or even encouraged (eg. for individuals with few items, the elderly, parents trying to simultaneously manage their children, etc.). In fact such acts may further strengthen group empathy and blame placed on the organization, and ultimately the stability of line constituency may be promoted. However, in AP settings, where ties are already tenuous, incidences of cutting are not likely to be welcomed. Associated perceptions of slippage are likely to be exacerbated, internal group blame advanced and retroactive jockeying (further line instability) may become still more likely. Hence a firm interested in better understanding the kinds of dynamic nuances they can anticipate in these settings would do well to understand the kind of group behavior typical in their particular context.

All of this is clearly relevant to any attempt to faithfully model waiting lines and overall service performance for these settings, and hence is clearly relevant in developing meaningful insights to practice. But the complex psychology and social dynamics here cannot be simply conjectured through untested assumptions. They must be empirically observed, their antecedents assessed and any shifts in perceptions of customers before and after jockeying must be documented for analysis. This implies the importance of field-based lab studies for such empiricism, followed by rigorous attempts to closely model these real-world dynamics for eventual incorporation in prescriptive analytical modeling approaches.

Of course it is worth emphasizing that group dynamics are not restricted to customers in supermarket operations. Hierarchical management structures tend to encourage group behavior among cashiers as well. These can engender cultures of trust as well as norms for both work motivation and blame, the nature of which no doubt interacts with group behavior witnessed among customers; That is, cashiers witnessing group phenomena in the form of mass jockeying are likely to develop psychological response norms and associated shifts in their own activity (eg. hastening their pace, perhaps with tradeoffs in accuracy). As with customers, depending on the GT or AP dispositions of these cashiers, work break downs, shifts in moral and overall changes in customer service may follow. These dynamics can spill over into the fundamental relationships between staff and management, where the most profound of operational difficulties may arise. The role that GT/AP and associated blame and work breakdown mechanisms may have among management planning teams (eg. those coordinating orders, marketing and staffing policies) and their staff can undermine the effectiveness of an operation on a grand scale. At these higher levels, we also start extending the implications of these group phenomena to larger intra- and inter-organizational systems.

5. System Dynamics in Operations

At an even higher level than individual and group behavior, system dynamics investigates the system-level effects of behavioral regularities, and designs ways to improve performance. Complexity in dynamic contexts consists of feedback processes, time delays, stocks and flows, and nonlinearities. System dynamics uses tools like causal mapping and simulation modeling. The former enables representation of the dynamic complexity, while the latter assesses the consequences of interactions among components of the system, information sources and individuals' decisions (Sterman 2000). System dynamics research addresses a number of operational issues, including inventory management (Sterman 1989a, Dielh and Sterman 1995), capacity investment (Sterman 1989b), new product introduction (Paich and Sterman 1993), production starts (Kampmann and Sterman 1998), project management (Lyneis et al. 2001), new product development (Ford and Sterman 1997, Repenning 2001), process improvement (Repenning and Sterman 2002), sales force management (Morecroft 1985), service management (Oliva and Sterman 2001) and fleet management (Moxnes 1998).

Traditional system dynamics models incorporate boundedly-rational individuals decisions (Simon 1959) as well as heuristics and biases (Tversky and Kahneman 1974), and examine their impact in complex dynamic settings, where the results of individuals' decisions change the future state of the system which then influences future decisions

(Forrester 1961, Sterman 2000). This body of knowledge focuses on the critical role of feedback, delays, stocks-and-flows and nonlinearity. System dynamics research suggests that decision makers perform poorly in environments with significant feedback delays (Sterman 1987, 1989a), feedback complexity (Diehl and Sterman 1995, Schweitzer and Cachon 2000, Sterman 1989a, 1989b), and changing conditions (Kleinmuntz and Thomas 1987). Behavior remains sub-optimal in dynamic environments, even when the decision maker has the opportunity to identify and correct errors (Hogarth 1981). Sterman (1989a, 1989b) suggests that poor performance in dynamically complex environments arise from people's misperception of feedback and, in particular, from individuals' insensitivity to the feedback that their actions create on the environment. In section 3, we used feedback to refer to "the transmission of evaluative or corrective information" resulting from a process (Merriam-Webster online dictionary), i.e., the emphasis is on the sharing of information and the salience, timeliness, frequency and relevance of the information shared. In this section, feedback refers to "the process by which a system… is modulated, controlled, or changed by the … response it produces" (Dictionary.com), i.e., the emphasis is on the complete path from the information shared to its consequences and back to the new information produced.

This section will present two types of misperceptions of feedback: structure and dynamics. Misperceptions of feedback structure are caused by mental maps that have a poor representation of the complexity of the real system; for instance, a mental model that ignores important feedback processes in the system. Misperceptions of feedback dynamics are caused by inaccurate mental models of how the system behaves. Here, a mental model that fails to capture the impact caused by accumulations will poorly infer their dynamics. A comprehensive review of previous work on misperception of feedback can be found in Sterman (1994, 2000). Diehl and Sterman (1995) explore feedback and time delay effects separately in an inventory management experiment to control for misperceptions of structure and dynamics.

5.1 Theoretical Facet 1: Misperceptions of feedback structure

A number of studies have demonstrated that individuals exhibit systematic dysfunctional behavior in dynamically complex environments (Kleinmuntz and Thomas 1987, Sterman 1987, 1989a, 1989b, Brehmer 1989, Moxnes 1998) and that this behavior persists in the presence of incentives, experience and the presence of markets (Paich and Sterman 1993, Diehl and Sterman 1995, Kampmann and Sterman 1998). Kleinmuntz (1993) concludes that decision makers are often "insensitive to the implications of feedback in dynamic environments" (p 223).

Sterman (1989b) suggests that the misperception of feedback arises from people's adoption of deficient dynamic mental models to guide their decisions. These deficiencies include an event-based perspective, focusing on specific events instead of the system structure that generates them; an open-loop view of causality where previous decisions lead to outcomes but do not change the current state; failure to understand the impact of delays and of accumulations by not separating cause from effect; and insensitivity to nonlinearities which alter the structure and behavior of the system.

Each of these misperceptions cause errors in decision making. Event-based and open-loop perspectives cause people to be reactive; to make the decision which would have been optimal under the previous conditions but which are suboptimal now. Delays and accumulations separate causes from effects and prevent individuals from learning from their past mistakes. Nonlinearities alter the strength of feedback processes over time, again preventing accurate attribution of outcomes to decisions. Multiple feedback loops, delays, stocks and flows, and nonlinearities are all important sources of complexity in systems.

Some of the errors above are due to a mis-match between an individual's understanding of the complex system and its actual structure. If an individual does not recognize a particular feedback process, his mental model of the system will not include an interconnection that in fact exists. For instance, a manager's mental model might assume that customer demand is independent of inventory availability, while in fact long delivery delays can influence customer demand. This mis-match will cause systematic errors in inventory decisions.

These system dynamics errors are common in operations management settings. Dana and Petruzzi (2001) find that when firms recognize the feedback of inventory availability on customer demand in a newsvendor setting they hold higher inventories. Gonçalves, et al. (2005) show that incorporating this feedback loop in a multitier supply chain model amplifies order variability, increasing the level of safety stock required to maintain a specified service level.

In the extreme, the failure to capture a feedback process can lead to an open-loop representation of a system, where previous decisions have no consequences for the current state. Research on cognitive maps finds that people often adopt open-loop models (Axelrod 1976, Hall 1976, Dörner 1980). These models lead to consistent external attributions. For example, as mentioned earlier, most participants attribute the cause of poor performance in the Beer Distribution Game to external causes rather than to their own previous ordering decisions (for more details on the game and it's associated dynamics see Sterman 1898a, 2000). These attributions are frequently followed by blame. Players infer that fickle customers or the other players' stupidity causes losses, instead of attributing the results to the structure of the distribution system. This prevents individuals from working to achieve a more accurate vision of the system in which they operate, or from taking actions to improve the system. Repenning (2001) and Repenning and

Sterman (2002) provide other examples of how the attribution errors can hinder efforts to improve new product development and process improvement efforts.

5.2 Theoretical Facet 2: Misperception of feedback dynamics

A second error in system dynamics is that individuals recognize the feedback structure (e.g. the existence of causal loops) but do not recognize the extent to which these loops will affect the situation. Bounded rationality tells us that people are limited in their abilities to solve complex problems (Simon 1957), but individuals often have difficulty mentally simulating even extremely simple models (those with easily conveyed structures).

As an example, consider an individual estimating exponential growth. Exponential growth is caused by the simplest possible feedback model: a single linear positive (or reinforcing) feedback loop. Wagenaar and Sagaria (1975) and Wagenaar (1978) found that participants forecast accurately in this task when the nonlinearities were small, and thus where linear extrapolation provides a reasonable approximation to exponential growth. When the growth rate and forecast horizons were large, however, individual estimates were extremely poor. The authors conclude that people underestimate rates of growth, extrapolating linearly instead of exponentially. Brehmer (1992) provides another example of the difficulty that people have estimating exponential growth. In a forest fire simulation capturing reinforcing feedback mechanisms that cause fires to spread, Brehmer found that subjects playing the role of fire chiefs often let their headquarters burn down. Note the difference between the misperception of the feedback structure (the existence of a loop) and the feedback dynamics (the strength of the effect). While participants knew that there would be a feedback effect, they significantly underestimated its impacts.

Misperception of feedback dynamics can influence a number of operational decisions. It directly impacts forecasting. Forecasters are likely to underestimate actual demand when demand grows exponentially, like the demand for a new hot product, and to overestimate demand when it falls exponentially, as in the case of the burst of a demand bubble. In capacity investment problems, the underestimation of exponential growth in demand might cause managers to invest too little in capacity to meet rising demand. In inventory problems, underestimation of exponential growth might lead to costly stock outs, as the rise in demand quickly outstrips the safety stock companies are likely to maintain. These estimation errors are systematic and tend to increase with the growth rates and forecast horizons.

Unfortunately, people's inability to form mental models is often even worse than reported above. Booth-Sweeney and Sterman (2000) and Sterman and Booth-Sweeney (2002) show that people fail to predict the dynamics of simple accumulations, characterized by a single stock, one inflow and one outflow (like a bathtub with water flowing in from the tap and out through the drain). These simple systems lack feedback loops, delays or nonlinearities. Despite the simplicity of the task more than half of the participants could not infer the dynamics.

Booth-Sweeney and Sterman (2000) suggested that subjects instead use a pattern-matching or correlation heuristic, matching the trajectory of the stock with that of the net flow rate. Cronin et al. (2008) attribute the poor performance in simple stock-flow tasks to a fundamental reasoning error that persists despite motivation, education level, context familiarity, and varied information displays. This correlation heuristic leads to a misperception of feedback dynamics and has important implications for operations managers. The bathtub task is analogous to plotting the trajectory of inventory (level) after being given information for production (inflow) and shipments (outflow). This setting also captures decisions in capacity management, where the stock of capacity is influenced by the inflow of capacity acquisition and the outflow of capacity loss. Hence, this result highlights challenges that individuals might face when intuitively making inferences about dynamic systems in very simply and commonplace OM settings.

5.3 Putting it together: System Dynamics

Several aspects of misperception of feedback structure and dynamics can systemically lead to operational problems in the grocery store setting with multiple checkout lines. Assume that customers buying primarily produce have easier access to the first two checkout lines, and poor visibility to other lines limits the amount of jockeying. A manager that has an event-based perspective may overreact when he observes a long line in front of the first two checkout lines. The manager may also fail to recognize that delays, like the manual inputting of produce codes, and accumulations, due to the limited jockeying, may lead to longer wait times. Nonlinearities, such as a missing or difficult to find produce code, may dramatically increase wait time for all customers in the queue. A manager that fails to recognize these dynamics may erroneously attribute the length of the checkout line to an employee's low productivity. Failure to recognize the structure of the problem may lead to a decision to open a new checkout line instead of improving access and visibility. Approaches to avoiding such failures would involve the development of an appropriate mental model of the system. For instance, instead of focusing on specific events, the manager could try to focus on the structure that generates the patterns observed and its specific occurrences, which would allow him to understand the role that delays, possible accumulations, and nonlinearities may have on the system. In addition, if the manager adopts a broader boundary – focusing not only on the performance of the queue with long delay, but also its disposition and the customer perspective - and a longer time horizon – to draw inferences on employee productivity – he would have more opportunities to gain insight the causes of particular behaviors.

Misperceptions of feedback dynamics, where managers may be aware of existing feedbacks, but may not understand their strength or time to play out can generate a self-fulfilling prophecy (Merton 1948). If long wait times persist in the produce checkout lines, patrons may be discouraged to shop in the store. Decreasing demand for produce may influence ordering and inventory decisions: the manager may place less frequent orders for lower amounts. As a consequence suppliers may shift priority to stores that order larger volumes with higher frequency, selling the remaining lower quality produce to the store manager. The combination of lower quality produce and reduced demand leads to longer residence time for produce, reducing remaining demand even further. If the manager fails to recognize that poor service (i.e., long wait times) cause demand to decrease and instead attributes it to any uncontrollable external factor, he will react and inadequately adjust his ordering and inventory policies. Again, here is where organizationally developed mental models of causes and effects can prove the most useful, if developed rigorously and applied appropriately to inform management.

In summary, OM models often ignore misperceptions of feedback structure and dynamics that can potentially lead to systematic operational problems. Understanding the proper feedback processes and adequately incorporating their strength can enhance the predictive power and performance of the resulting OM models.

6. Conclusions and Directions for the Future of Behavioral Operations

Research in operations management is inevitably faced by limitations in the scope and depth of our studies. This implies the need for hard decisions on where to focus our attention. Simple models are easy to solve, but are likely to be less descriptively accurate than more complicated models (when such complication can be appropriately justified). We believe, in particular, that incorporating human behavioral factors into OM models and empirical research will provide gains not only to the practical nature of existing theoretical models but also to the field's general understanding of what it means to have effective operations.

A greater appreciation of human behavior in future OM work can take many forms. For example, operations systems which are robust to overconfident agents, models which examine what goals *should* be, as well as what currently *are*, policies to alleviate blame spirals, and systems to help individuals recognize feedback loops all represent the gains to be had from incorporating behavioral factors into OM. Field based action studies, natural experiments and lab experiments can help in developing and refining our models.

While much of the existing research has focused on how a failure to include behavioral influences can lead to operational systems which fail, we believe that future research and practice-oriented models can be more constructive by designing systems which are robust to heuristics and biases, lack of motivation or inappropriate goals, groupthink or blame spirals, unanticipated feedback loops or unexpected dynamics. It is worth pointing out that much of the relatively early work on the role of human behavior in OM has focused on the identification of behavioral gaps between normative models and descriptive data. The next steps in the evolution of this literate should clearly be focused on explaining the causes of these gaps, measuring their impacts and attempting to redesign systems, policies and institutions to either counter-act or at least provide accountability and adjustability for behavioral causes.

On this last point it is critical to emphasize that we are in no way suggesting that the goal of identifying characteristics and anomalies of human behavior in OM contexts is strictly to devise ways to limit the impact of behavior in general. Behavior that brings about outcomes outside of the norms and expectations of existing conceptual models (empirically motivated or otherwise) may actually be desirable – take for example the many cases of individual ingenuity and rapid emotional response known to be the salvation of firms in moments of crisis.

With this in mind, a sensible stream of inquiry for future work should remain fundamentally an open and flexible one. It should involve answering questions such as "can this observed (though perhaps unanticipated result) be linked specifically to human behavior?", "can one expect to see such a result in future related contexts? – ie. can we change the conceptualization of this effect from an 'unanticipated' one to one we can in fact expect?", "can we leverage our understanding of the dynamics associated with this behavior in ways to either reduce its likelihood or magnitude of impact?", "if a positive effect, can we put in place procedures that increase its likelihood so that its benefits can be relied upon robustly across a range of scenarios?".

In other words, our efforts as researchers should focus on simply *making the most* of an increased understanding of human behavior. This suggests caution on the part of researchers to avoid fundamental disciplinary biases. The reality of human behavior, and its implications for research and practice, should not be viewed generally as either bad or good. Instead research into these topics can probable best proceed intelligently through an openness to new ideas, divergent opinions and observed anomalies that challenge past notions and may have the potential to break new ground in our view of practice and prescription.

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