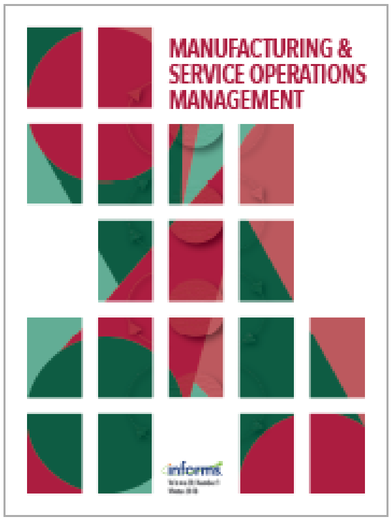

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20th Anniversary Invited Article

Behavioral Operations: Past, Present, and Future

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Abstract. Behavioral operations is now an established and fundamental research field dedicated to understanding how the behavior of managers, workers, and customers influences operational decisions and outcomes. Just 20 years ago, behavioral research within operations management was relatively small and dispersed. *Manufacturing & Service Operations Management* has played an integral role in the field's development since then through its openness to new research questions and methodologies. In this article, we reflect on the research goals pursued in behavioral operations as well as the operational contexts explored. We also share thoughts on promising areas for future research.

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Keywords: behavioral operations • firm-level behavior • supply chain behavior • customer behavior • multi-methods • historical perspective

1. Introduction

Behavioral issues impact pretty much all decisions that we face during our lifetime. For most of us, *social preferences*, such as fairness, trust, and trustworthiness, matter in our personal and professional relationships. We do not necessarily update our beliefs in a Bayesian fashion when we receive information from our close trusted allies, friends, or family. We perhaps follow a Bayes-like rule if we were to receive the same information from an untrustworthy individual. We sometimes go out of our way to help others when we perceive outcomes to be fair (or penalize them otherwise), even when doing so is costly to us. We are different from each other and have *individual preferences* and traits. Some of us are risk takers and enjoy playing Texas Hold'em, while others prefer to spend their vacation bird watching. Some of us are also overconfident in our perceptions and actions (not the authors, of course!). We regret decisions already made or actions not taken. We are also *boundedly rational*. Some of us are better at understanding the consequences of our actions on future payoffs (and can delay gratification). Others are better at understanding the consequences of their actions on their partners and their partners' responses to them (and hence, may be better chess players). We, at least the authors, make mistakes and are not perfect optimizers when it comes to making professional and personal decisions. Instead, we often follow simple heuristics even when stakes are high (such as allocating 80% of our retirement savings to stocks and 20% to bonds or some managed accounts and hoping for the best). Our decisions are, therefore, often influenced by our social and individual preferences as well as limits in our rationality.

People, who are somewhat like us, design, manage, and optimize processes within and across organizations. From high-level executives to line managers, people issues play a major role in the effective design and management of global value chains involving both manufacturing and service operations. We, as quantitative scholars trained in operations research and management sciences, can study, analyze, and quantify the impact of such behavioral issues on operations. Why? Because if we do, then we can (1) describe and better understand whether, why, when, and how normative models (based on economic objectives, such as expected profit maximization) deviate from actual observed behavior; (2) use these observations to design better predictive models and algorithms; (3) utilize these enhanced predictive models and behavioral understanding to prescribe and optimize operational decisions arising in actual business contexts ranging from retail to healthcare operations; and (4) improve decision outcomes by designing related operational processes to nudge people to choose close-to-optimal decisions or actions. In other words, understanding the role of behavior in operations can help us and businesses to design robust operating systems that account for (or actually embrace!) the behavioral tendencies of managers, workers, and customers.

The recent explosion of interest in behavioral research in operations management (OM) began roughly 20 years ago, around the same time that *Manufacturing & Service Operations Management* (*M&SOM*) was first released. A coincidence or not? Although we leave that to others to debate, it is clear that *M&SOM* has played an important role in cultivating interest in behavioral research. Early on, the journal featured an invited review that laid out a framework for behavioral research at the interface of operations and human resource management (Boudreau et al. 2003). This was followed a few years later by a call for a special issue on behavioral operations edited by Rachel Croson and Noah Gans and published in the fall of 2008, one of the first in the field. The issue presented seven insightful and thought-provoking papers by Bearden, Murphy, and Rapoport (2008); Bostian, Holt, and Smith (2008); Chen, Kaya, and Özer (2008); Gino and Pisano (2008); Katok, Thomas, and Davis (2008); Su (2008); and Wu, Loch, and der Heyden (2008). These papers are now highly referenced and, even then, represented a wide range of behavioral research questions and operational contexts. *M&SOM* has also supported the development of influential reviews that advocate the need for a deeper understanding of how workers, managers, and customers behave and make decisions within operations settings (Bitran et al. 2008, Gino and Pisano 2008).

Our goal in this paper is to celebrate what we have learned about behavior in manufacturing and service operations contexts, sampling from extant research in behavioral operations. In addition, we argue that behavioral operations is a fundamental area of research, not just an application of behavioral economics or psychology. The OM field provides rich contexts for studying important and relevant microlevel people issues and promoting foundational understandings of behavioral concepts. In Section 2, we illustrate the main types of research questions asked and research goals pursued by behavioral operations scholars, focusing on two problem contexts fundamental to OM. In Section 3, we discuss and illustrate more broadly the wide variety of operational decision domains for which behavioral research is instrumental. In Section 4, we further expand on behavioral operations research goals using a simple categorical framework. Within each section, we also look forward to the future to provide our opinion on what lies ahead. We conclude our thoughts in Section 5.

2. Behavioral Operations Research Goals

To help illustrate the types of research goals pursued by behavioral operations scholars, we first focus on two examples. The first represents a fundamental operational decision faced by managers within a firm, and the second considers strategic interactions among managers in decentralized supply chains. Through these examples, we also demonstrate how scholars collectively build on each other's work to form fundamental contributions to behavioral operations.

2.1. The Case of Newsvendor

One of the most well-known and well-studied firm-level operations problems is planning under demand uncertainty. The classical representation of this planning problem in operations is the newsvendor model. This model provides an important building block to study more complex decisions across a wide variety of problem domains: for example, strategic capacity investment, optimal time to invest as in real options, incentive or contract design in supply chains, and many others. Given the prevalence of this problem, would you not be curious to know what a person charged with such a decision will actually do? Schweitzer and Cachon (2000) were curious, and therefore, they conducted laboratory experiments to find out. They found that observed newsvendor behavior significantly deviates from what the normative newsvendor model predicts. Specifically, the participants' ordering decisions are systematically pulled toward mean demand and away from the "optimal" ordering decision that balances the cost of holding excess inventory and the cost of missing demand. They called this phenomenon the "pull-to-center" bias.

A group of scholars during the past two decades investigated whether this pull-to-center bias was a fluke or exists more broadly. Now, we know that this behavioral bias is robust across different cost parameters, demand distributions, learning schemes, procurement experiences, types of information provided to participants, and even different cultures (Benzion et al. 2008, Bolton and Katok 2008, Lurie and Swaminathan 2009, Bolton et al. 2012, Özer et al. 2014). Researchers have also tried to uncover reasons why such a bias persists. We know that this bias cannot be explained by, for example, risk preferences, waste aversion, or stockout aversion (Schweitzer and Cachon 2000). Instead, people anchor their decisions to the mean, they chase (realized) demand, they make mistakes in decisions, they minimize ex post errors, and/or they are overconfident and perceive variability to be smaller than it actually is (Schweitzer and Cachon 2000, Bostian et al. 2008, Su 2008, Ho et al. 2010, Kremer et al. 2010, Ren and Croson 2013). There is yet to be a unifying theory to describe why people behave differently from what the normative theory predicts. What we are certain of at this point is that people are predictably "irrational" when it comes to planning under demand uncertainty. These studies collectively establish an accumulated body of knowledge that better describes and predicts how people make such planning decisions in various environments.

Given these advancements, managers can consider developing ways to utilize this knowledge of newsvendor behavior to improve decisions. For example, Becker-Peth et al. (2013) analyze how a buyback contract should be designed to account for behavioral biases in newsvendor decisions and demonstrate that such a contract outperforms contracts designed when ignoring the biases. Other studies examine potential interventions to help managers in the newsvendor role to make better decisions: for example, fix ordering decisions for a longer planning horizon (Bolton and Katok 2008), separate demand forecasting from the ordering decision and provide a decision support tool (Lee and Siemsen 2017), or use more effective (yet normatively equivalent) inventory measures (such as days of supply) rather than inventory turn rate (Stangl and Thonemann 2017). One may ask why we should care about behavior in such operational decisions given advances in information technology, data sciences, and artificial intelligence. Can such decisions not simply be automated and made by "smart" algorithms rather than humans? Our response is that more research in this direction is needed to understand whether, when, and how humans and decision automation will coexist to provide superior operational results compared with algorithms or humans alone (see Flicker 2019 for a recent discussion on this topic).

2.2. The Case of Supply Chain Information Sharing

At the supply chain level, one of the most actively studied problem contexts is information sharing in a decentralized supply chain. This literature has focused extensively on addressing inefficiencies caused by asymmetric information, local optimization, and conflicting incentives (see Ha and Tang 2017 for an extensive review). One possible remedy is to design incentive-compatible contracts or mechanisms to align incentives and induce truthful/credible information sharing. Özer et al. (2011) instead examine the problem through a behavioral lens. They were curious whether and when firms resort to trust and trustworthiness when incentives are not perfectly aligned. They contend that managers in these supply chains do not always—in fact, most of the time do not—behave as *homo economicus*. We, homo sapiens, put ourselves in a vulnerable position by trusting (when standard economic objectives suggest otherwise) in anticipation that our trusted partner, another homo sapiens, will be trustworthy. We feel bad and incur a disutility when we deviate from the truth or when our actions may harm others. We care about others' wellbeing and strive to be trustworthy. We also anticipate that such social preferences may help us coordinate our decisions and therefore, often lead to better outcomes. Inspired by these ideas, these authors conducted a series of laboratory experiments with human subjects and observed that people indeed demonstrate trusting and trustworthy behavior in a supply chain context. As a result, they are more cooperative than what normative models predict. In particular, people tend to share trustworthy, useful information, and they trust the information being shared to some extent when making investment decisions. The authors go on to study how the supply chain environment affects such trusting and trustworthy behavior.

The work by Özer et al. (2011) stimulated a group of curious OM scholars to expand this investigation to better understand when, why, and how trust plays a role in affecting information sharing and cooperation in a variety of decentralized supply chain contexts. We now know that humans' tendency to trust (or not) influences supply chain outcomes in various interaction settings, such as assembly or just-in-time systems, across different cultures, across organizational silos (such as sales and operations), when teams as opposed to individuals are making decisions, and in interactions involving experienced professionals (Hyndman et al. 2013, Inderfurth et al. 2013, Özer et al. 2014, Beil et al. 2018, Scheele et al. 2018, Choi et al. 2019). We have also accumulated evidence to better predict how trust in supply chains may be affected by environmental and institutional factors. For example, financial vulnerabilities and market uncertainty are barriers to trust; competition can impede trust, and making relation-specific investments without a binding agreement signals trustworthiness and engenders trust from supply chain partners (Özer et al. 2011, Spiliotopoulou et al. 2016, Beer et al. 2018). In the meantime, factors of trust and trustworthiness are being incorporated in traditional OM models to more accurately predict behavior and better prescribe managerial strategies (Özer et al. 2011, Ebrahim-Khanjari et al. 2012, Scheele et al. 2018).

Almost a decade of active research has yielded a cumulative body of knowledge that equips us with invaluable and actionable strategies to establish and utilize trust and trustworthiness to improve the efficiency of supply chains (see Özer and Zheng 2017 for a unifying framework). For example, blinded reviews can better encourage honest feedback and promote trust in review systems for online marketplaces (Bolton et al. 2013). Western companies can appoint a fixed contact person and limit management rotation when transacting with Asian partners to embrace their collectivist culture and enable trust (Özer et al. 2014). Similarly, a Western marketplace company (such as eBay) when operating in Asia must invest even more in collaborative technologies (such as chat and video-conferencing functionalities) to help establish trust and trustworthiness, leading to credible information sharing among Asian participants (Özer and Zheng 2019). Suppliers can gain retailers' trust and successfully secure procurement contracts by improving factory working conditions (Liu et al. 2019). Directly soliciting information, as opposed to delegating decision to the party with superior information, promotes truthful information sharing as well as trust in the information provided (Özer et al. 2018).

This growing body of knowledge represents only the tip of the iceberg regarding the role of trust and trustworthiness in supply chain interactions. Many interesting questions still remain. For example, how do managers' prior work experience, attitudes toward risk, or even gender and socioeconomic backgrounds affect their tendency to trust or act trustworthily in a business context, such as procurement? How do market factors, such as investment costs, demand uncertainty, and length of relationship, influence the presence or significance of trust in supply chains? How should we embrace different cultural traits to establish trust and trustworthiness, especially in global supply chains that cross country borders? How can we leverage social networks to enhance trust and trustworthiness within and across organizations? How do personnel change and management rotation affect the evolution of trusting relationships? This vast area of research presents exciting opportunities for behavioral operations scholars to collectively and iteratively study the role of trust in supply chain and other operational contexts.

To summarize, we witness with both the newsvendor and the supply chain information sharing examples four key goals of behavioral operations research: to more accurately *describe* and *predict* how people make operational decisions and to *utilize* the resulting knowledge of behavior to *improve* decisions and system design. It is through the *iterative* pursuit of these goals that behavioral operations as a fundamental research area contributes to the theory and practice of management sciences.

3. Behavioral Operations Problem Contexts

Having provided an understanding of the range of goals that behavioral operations research strives to achieve, we turn now to a broader view of operational decision contexts beyond the two examples just described. We organize the discussion along three categories: firm-level decisions, supply chain contexts, and the customer perspective. The subsequent discussion is by no means a comprehensive review of the literature, but rather, our attempt to illustrate the significant role of behavioral research in OM with a selective sample of studies. Readers interested in a comprehensive literature review are referred to the recently published *The Handbook of Behavioral Operations* (Donohue et al. 2019).

3.1. Firm Perspective

As one of the building blocks in OM research, inventory decisions, particularly those within the newsvendor framework, represent the focus of the earliest foray in behavioral operations studies (Becker-Peth and Thonemann 2019). As illustrated in Section 2.1, this line of research exemplifies how a group of researchers engage in an iterative process of establishing and refining cumulative knowledge about newsvendor ordering decisions made by humans. The vast majority of this literature has focused on describing and predicting behavior more accurately than the normative theory. Only recently did a handful of studies emerge to develop interventions to counteract undesirable behavioral biases and improve decisions. We advocate that more research be pursued in this direction. In addition, researchers are encouraged to explore richer inventory decision contexts, such as multiechelon and multilocation systems, to continue to strengthen the practical values of behavioral inventory research.

Another building block of OM centers on process and capacity analysis, with queueing theory as a major analytical toolbox. This stream of research increasingly takes a behavioral perspective as the analysis of service systems—where both customers and servers are mostly humans—gains significance. Because of the prominent presence of humans in service systems, even the theoretical models have inevitably developed to account for a rich set of parameters that represent customer and server behavior (Whitt 1999, Garnett et al. 2002, Kostami and Ward 2009, Liu et al. 2010). Within the specific context of call centers, Gans et al. (2003) outline a portfolio of important research directions that include better understanding and modeling customer and server behavior. In addition, *M&SOM* published an OM forum article by Bitran et al. (2008) with the intent of bridging the gap between queueing theories in OM and behavioral findings in marketing and psychology. We refer readers to Allon and Kremer (2019) for an excellent review on the development of behavioral queueing research.

Much of the theoretical queueing models developed to date focus on rational behavior (for example, assuming that customers can correctly estimate waiting time or that their behavior can be characterized by exogenous parameters [such as probability of abandonment] that are not affected by the service environment). A handful of recent studies have started to move beyond the rationality regime. For example, Huang et al. (2013) develop a bounded rationality model of customers who cannot correctly estimate waiting time and analyze how system performance may be affected as a result. Lu et al. (2013) empirically study how waiting in queue affects consumers' purchase behavior in a retail store. They find that consumers focus mostly on queue length without sufficiently adjusting for the service rate. Hence, a long but fast moving queue may be perceived as overly undesirable by consumers compared with what the theory would predict. In line with these observations, Tong and Feiler (2017) develop a new behavioral model of forecasting and show that people tend to overestimate (underestimate) the true wait time variance for long (short) queues. Using data from an emergency department, Song et al. (2015) study the impact of a pooled queue versus dedicated queues on the patients' waiting time and length of stay (LOS). They show that both waiting time and LOS decrease with dedicated queues, because physicians with dedicated queues demonstrate stronger ownership and manage the flow of patients in their queues more proactively. These studies begin to present interesting challenges to canonical queueing theory results: for example, the benefit of queue pooling. In our view, behavioral research as related to service systems, particularly research concerning boundedly rational human behavior, is still in its infancy. We encourage more empirical and experimental work to better understand behavior in various environments, which should then help researchers develop more realistic models to optimize system design and guide behavior for better system performance. With increased availability of data, we also call for more research in important application domains, such as healthcare, retail, cloud computing, and so forth. Within this special issue, KC et al. (2019) and Keskinocak and Savva (2019) provide an excellent discussion on the recent surge and future prospects of research in healthcare operations. Donohue and Schultz (2019) provide a glimpse of behavioral research recently explored in both healthcare and retail operations along with ideas for future studies.

Somewhat related to the above stream, another area of within-firm OM decisions for which behavioral research has arisen considers employee management. Boudreau et al. (2003) present one of the first calls for research to bridge the gap between OM and human resources management. As an early foray, Schultz et al. (1998, 1999) examine within the context of lean operations how worker behavior and motivation change in a low-inventory environment that ultimately promotes productivity. Focusing on when frontline workers take initiative to improve their work systems, Tucker (2007) shows that managers should create an environment where it is safe to talk about failures and where management proactively responds to workers' communication about failures. In a similar vein, Siemsen et al. (2009) empirically examine antecedents of psychological safety and how it can be enhanced to motivate employee knowledge sharing. More recently, Gopalakrishnan et al. (2016) examine how servers in a service system may adjust their work rates based on different workload incentives and develop models to characterize such behavior, prescribe system-optimal staffing/routing policies, and evaluate the resulting system performance. Song et al. (2018) show in an emergency department setting that making performance feedback public leads to increased productivity of healthcare providers. Research in this area remains sporadic. Therefore, we are in need of a more systematic body of work that examines behavior in various workforce contexts and develops accurate models to inform system design. In addition, with the rise of self-scheduled workers in on-demand platforms (such as Uber and Lyft) or freelancing platforms (such as Upwork), as well as increasing applications of robotics, our field can play a significant role to better understand worker behavior and motivate worker engagement in these new environments to guide the design of more efficient and productive systems.

3.2. Supply Chain Perspective

Behavioral research in a supply chain context begins with the seminal work by Sterman (1989), who used the well-known beer distribution game to study the bullwhip effect and identify supply line underweighting as a contributing behavioral factor. Results from numerous replications of the game and its variations demonstrate the same operational and behavioral challenges related to decision making in a decentralized supply chain (Croson and Donohue 2006, Croson et al. 2014, Moritz et al. 2019). These include lack of information sharing, underweighting of the supply line, failure to coordinate decisions, local optimization of individual incentives, and distrust among supply chain partners, many of which are the central topics of subsequent supply chain management literature. In addition to the literature on supply chain information sharing discussed in Section 2.2, behavioral operations researchers also investigate the performance of theoretically optimal contracts when the relevant decisions are made by humans. Chen and Wu (2019) offer a comprehensive review of this behavioral buyer-supplier interaction literature.

These studies have shed light on a number of behavioral factors that influence the performance of different contracts. For example, Cui et al. (2007) establish that fairness concerns by the supply chain partners allow them to coordinate the supply chain even under a simple wholesale price contract. Ho and Zhang (2008), Katok and Wu (2009), and Zhang et al. (2016) study how loss aversion affects channel outcomes of buyback, revenue sharing, and two-part tariff contracts. Zhang et al. (2016) also offer insights on when a buyback contract may outperform a revenue-sharing contract (and vice versa) if the party setting the contract is loss averse. This stream of research is evolving from descriptive to being more prescriptive to inform how contract design in practice should take into account relevant human behavioral factors. More recently, a few studies further extend this research to examine human behavior in the bargaining process and how it affects the ultimate channel outcomes (Leider and Lovejoy 2016, Davis and Hyndman 2019, Haruvy et al. 2019). These studies signify the trend of behavioral research helping to close the gap between theory and practice by examining richer decision-making processes.

There are many important open questions in supply chain management that present rich opportunities for behavioral research. For example, more research is needed to better understand the role of social preferences, such as trust, fairness, and reciprocity, in coordinating decisions and information in more complex supply chain environments. We also call for research that broadens the types of problem domains being studied, such as sourcing strategies, risk management, capacity or inventory allocation problems, channel competition or integration, collaborative innovation, and many others. We have seen a few pioneering works in some of these domains, including Chen et al. (2008, 2012), Gurnani et al. (2014), and Cui and Zhang (2018). We encourage future research to expand on both the decision domains and the behavioral preferences being investigated. This expansion will help to offer a cohesive body of knowledge to better describe, predict, and improve human decisions in supply chains. It will also help to inform theory development that would enable the design of more efficient supply chains in practice when important behavioral factors are present.

3.3. Customer Perspective

In recent years, the OM field pays increasing attention to understanding and modeling the customer or consumer perspective in operations settings, and the concept of the total value chain gains growing interest. This development opens up a fruitful avenue for behavioral research. Perhaps because of the considerable amount of consumer behavior research that already exists in other disciplines, such as economics and marketing, behavioral operations research in this area has taken a strong modeling focus. Take pricing and revenue management (PRM) as an example, researchers have captured in canonical PRM models various behavioral regularities of the consumers, such as loss aversion (Popescu and Wu 2007, Nasiry and Popescu 2011, Baron et al. 2015), dynamic inconsistency (Su 2009, Baucells et al. 2017), anticipated regret (Nasiry and Popescu 2012, Özer and Zheng 2016), probability misperception (Özer and Zheng 2016), and anecdotal reasoning (Huang et al. 2017). These more realistic consumer (and hence, demand) models allow OM scholars to better predict market outcomes of different PRM strategies and in turn, provide invaluable insights for optimizing such strategies. Özer and Zheng (2012) and Ovchinnikov (2019) provide extensive reviews of this literature.

Beyond the more developed behavioral research related to PRM, we observe a few new trends and developments. First, sustainability is another application domain for which research on consumer behavior is emerging. For example, Ovchinnikov (2011), Abbey et al. (2015), and Agrawal et al. (2015) study consumers' perceptions of the quality of remanufactured products and how these perceptions impact the economics of remanufacturing. Kraft et al. (2018) examine consumers' valuation of a company's social responsibility initiatives and how it depends on the level of supply chain visibility and the consumers' prosociality. Buell et al. (2019) investigate how relative performance transparency can be utilized to motivate sustainable choices. Second, with growing prevalence of digitization in consumers' daily activities, a unique opportunity of behavioral research driven by large-scale field data has arisen. For example, Moon et al. (2017) utilize detailed consumer tracking data from a retailer's online channel to develop a consumer model of price monitoring and demonstrate the benefits of a randomized markdown policy in the presence of such monitoring. Cohen et al. (2017) and Cohen-Hillel et al. (2019b) estimate from transaction data a demand model that captures consumers' limited memory on historical prices (or the lowest price in the past) and optimize the retailer's promotion planning based on such data-driven, behaviorally informed demand models. Third, a handful of researchers have started to leverage field experiments to examine how consumers respond to changes in operational design and decisions as well as to measure the resulting business impacts. For example, Buell et al. (2017) use a combination of field and laboratory experiments to demonstrate that providing operational transparency between producers and customers both improves customer perceptions of service value and enhances service efficiency.

Customers are an essential part of the total value chain. New business contexts, such as online retailing, sharing or circular economy, two-sided markets, crowdsourcing, mobile advertising, and social media, are revolutionizing how organizations interact with their customers as well as how customers interact among themselves. In some of these innovative models, customers are also themselves producers: for example, when organizations utilize innovation contests to enhance Research and Development (R&D) beyond relying on internal talents and when independent producers (especially in developing economies) leverage knowledge-sharing platforms to learn and promote new technologies. These developments present exciting opportunities for impactful behavioral research.

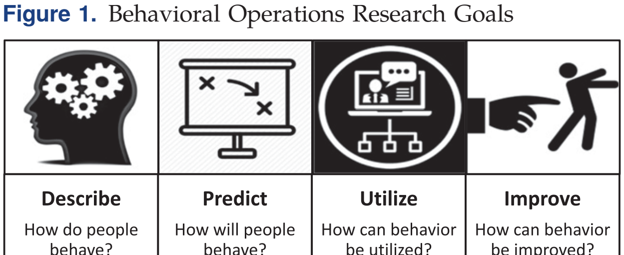
4. Revisiting Behavioral Operations Research Goals

We hope that our brief overview of behavioral operations research goals and problem contexts helps solidify how the field has grown since *M&SOM* began and some of the exciting areas for future research. Our objective in this section is to reflect more generally on the research goals that emerged in our discussion of the newsvendor and supply chain information sharing contexts in Section 2 and provide additional insights on how scholars can continue to push toward these goals. For simplicity, we organize behavioral research goals into four categories (describe, predict, utilize, and improve), with the understanding that a given paper may straddle multiple categories. Figure 1 illustrates this framework.

Research within the describe category aims to provide a more accurate depiction of how humans make decisions, perform tasks, or otherwise behave in operational contexts. Research in this category often focuses on identifying whether, when, and how behavior deviates from normative theories and then offers behavioral theories for why such deviations occur. These types of research are a logical starting point when the operational context involves a decision that is reasonably well defined: for example, decisions concerning how capacity-, inventory-, or pricing-related parameters are set, how jobs are allocated across workers or demand is allocated across suppliers, or how supply chain partners decide what information to share with each other. In such cases, it is natural or perhaps, even necessary to begin exploration by crafting a normative model of the decision and using this model as a benchmark for comparison against actual behavior revealed in a laboratory experiment or field setting.

However, what if there is no immediately available normative theory to begin with? In other words, what if the behavior of interest is not the outcome of a decision comparable with an immediately available benchmark of what is perceived to be "rational" or "optimal"? For example, research focused on developing better descriptions of worker motivation, customer satisfaction, or manager compliance. Studies of these topics often start with empirical exploration, which helps to inform a behavioral theory that can be tested through primary or secondary data, perhaps in concert with behavioral experiments. We have already pointed out a few papers of this nature (Tucker 2007, Siemsen et al. 2009, Song et al. 2018) but believe that this is an exciting area of future growth within the describe category. The *M&SOM* journal can cultivate more inquiries of this type with hypotheses that are grounded in evidence-based research and theories (including empirical, psychological, behavioral, simulation, and other).

Figure 1. Behavioral Operations Research Goals



Research within the predict category tests the predictive power of a behavioral theory. The goal here is to design enhanced models and algorithms that better capture our refined understanding and description of observed behavior. Many papers that introduce a behavioral theory also include some elements of prediction testing, essentially spanning both describe and predict categories. However, there is also room for prediction to take center stage as the primary research focus. Refining boundary conditions for a previously introduced theory is an important contribution in its own right. Some examples include Nagarajan and Shechter (2014), Long and Nasiry (2015), Cohen-Hillel et al. (2019a), and Li et al. (2019). Prediction-focused research helps separate out which behavioral theories are robust to different situations and, in the process, often identifies a new attribution that provides a deeper understanding of the underlying mechanisms.

Although theory building and refinement are important and exciting areas of research, there can be a tendency among OM scholars to jump to new theories or problem contexts before sufficiently fleshing out the boundaries of an existing theory. The replicability of experimental outcomes has recently emerged as a hot topic in other social science disciplines, including psychology and behavioral economics. An article published in *Science* shined a strong light on this issue through a replication study of 100 published psychology studies within three key psychology journals (Open Science Collaboration 2015). The authors found that only 36% of the replications yielded statistically significant results.[1] To guard against such outcomes, let us be cautious about pushing the study of "new" OM contexts and problem domains as the only novel or interesting research objective. Replication studies, together with their extensions, can serve the purpose of exploring further and uncovering new and novel insights on already explored, yet fundamental and important, OM problems. The behavioral literature on newsvendor decisions (as previously discussed) provides an excellent example of how scholars can build on each other's work and provide new insights into the boundary conditions of a behavioral theory.

Similarly, scholars may use replication studies as an anchor point to explore exciting new research questions relevant for operations management.

Prediction research can also involve testing whether competing behaviorally informed analytical models are consistent with behavioral data. It is important to note that such association alone may not imply causality. Additional analysis (for example, controlled experiments that isolate the link between cause and effect) is often needed to uncover such a relationship. This line of research can also establish behaviorally accurate, yet still parsimonious, models in one context and show, for example, how such models can be used as input for informing other OM decisions: for example, more behaviorally accurate models of how customers react to the timing and level of markdown pricing, how suppliers react to contract types, or how workers react to different incentive schemes. These results can then be used, for example, to better design operating systems.

Research in the utilize category examines how operating systems can be redesigned, or managerial decisions can be altered, to leverage behavioral knowledge for the benefit of all (or at least some) stakeholders in a value chain. Because OM is an applied field, it is important to move beyond describing and predicting behavior to prescribing and optimizing operational decisions that capture behavioral issues accurately while keeping an eye on the "well-being" of stakeholders. Utilizing behavior may initially appear somewhat unseemly, because it raises the possibility of undermining the best interests of those whose behavior is being studied. That may be true in some cases. Hence, when incorporating a more accurate representation of behavior into OM decisions, we can also investigate when using such behavior leads to better outcomes for all stakeholders, including other living beings (such as in the case of environmentally responsible supply chains; e.g., Agrawal et al. 2015, Buell et al. 2019, Buell and Kalkanci 2019). For example, if a more behaviorally accurate model of consumer reaction to markdown pricing is incorporated into a markdown pricing algorithm, the timing of markdown pricing may be adjusted in a manner that leads to higher efficiency for the channel. This increased efficiency implies cost savings that could be shared with consumers through lower initial prices as well as waste reduction that could benefit, for example, marine species. We believe that there are exciting opportunities to utilize a behaviorally informed model in various operational contexts and decisions, such as inducing environmentally and socially responsible production and consumption (Muthulingam et al. 2013, Agrawal et al. 2015, de Zegher et al. 2018, Kraft et al. 2018).

Research within the improve category differs from the utilize category in that it focuses on developing mitigation strategies that help people make better decisions in the first place. Such research can help redesign business processes to influence people in their behavioral tendencies and/or guide them to choose close-to-optimal decisions or actions for desired outcomes. This exciting category of research is still in its infancy within behavioral operations. One approach for improving behavior is to engineer and design business processes that cultivate the desired behavior (for example, increase trust and trustworthiness), leading to cooperation (see Özer and Zheng 2019). An immediate example is how to design reputation/feedback mechanisms used by online vendors (for example, resellers at Amazon or eBay) or service providers (for example, taxi, restaurant, haircut, and healthcare). A well designed reputation system can reduce the buyer's (trustor's) vulnerability owing to uncertainty governing the actions of the seller (trustee).

Another approach to improving behavior, popularized by Thaler and Sunstein (2009), is to nudge people toward better decisions. The underlying idea is to use knowledge about how people make decisions to design choice architecture that helps people choose outcomes that are in their self-interest. Examples of changes in choice architecture that can improve decision outcomes include reducing the number of alternatives (reducing choice overload) and emphasizing future events (overcoming present bias). Our field has produced many prolific scholars who analyze, design, and improve processes in various operational contexts. We envision that a wide variety of OM contexts will enable scholars to determine and document innovative ways (either by influencing behavioral tendencies or by nudging actions) to improve operating systems, also resulting in exciting research opportunities.

We hope that this categorization of research goals will be helpful for future scholars who strive to describe and predict behavior of workers, managers, and customers more accurately and utilize the enhanced knowledge of human behavior to improve decision making and system design. Achieving these goals will naturally require a variety of research methodologies. Luckily, scholars working in behavioral operations have historically used a wide variety of methodologies in their research. Laboratory experiments in combination with field validation are helpful in describing behavior. Such empirical observations along with analytical models help to characterize how behavior differs from normative theory. Predicting behavior, and further prescribing managerial strategies and system design, often benefit from a cyclic approach. Here, one may start with a behavioral model informed by prior research. This model is then used to develop hypotheses about how the behavior (for example, the pull-to-center bias or trust and trustworthiness) will influence operational outcomes under different conditions. These hypotheses are next tested using laboratory experiments or other empirical data. The outcome of this data analysis may uncover possible gaps in the original description of the behavior, leading to additional work capturing these nuances through another informed behavioral model. The resulting refined model serves as the basis for designing new strategies and systemic elements to improve operational outcomes, and the cycle continues. This cycle between analytical, experimental (including both laboratory and field-based settings), and empirical methodologies lies at the heart of behavioral research and is important for the development of robust behavioral theory.

The emergence of new sources of data, particularly "big" data that depict individual reactions to different operational decisions, is an exciting development for behavioral operations in the future. Advances in information technology and management have enabled organizations (as well as scholars) to collect and process enormous amounts of data regarding individuals' actions/decisions each and every minute from a variety of operational contexts. We no longer only need to imagine or perceive what people (for example, managers, workers, and consumers) think or may do when we model their objective functions and decisions. In fact, we can observe (often in real time) their actual decisions in the field as well as in controlled environments. Such levels of detailed observations can help us as management scientists and operations researchers define, measure, and quantify directly from observed actions whether and why a certain behavior persists. As a result, we can also develop tangible definitions of behavior (other than the psychological definitions, which are often difficult to operationalize). See Özer and Zheng (2019) for an example on the definition of trust and trustworthiness. Developing tangible definitions and actionable models is useful in operationalizing such behavioral issues to effectively manage operations (as in the cases of predictably irrational newsvendor and establishing the role of trust in supply chains). We expect that methodologies, such as machine learning and agent-based modeling, will be used more in the future to help describe new behavioral tendencies and predict, utilize, improve, and test the impact of improvement strategies.

5. Conclusions

Behavioral operations is a fundamental area of research (and not just an application of behavioral economics or psychology) for at least the following reasons. First, to understand, model, and quantify behavior of individuals requires one to study them in a relevant context. Behavioral issues, such as fairness, trust, and rationality, mean very little in the abstract; a problem context is needed to make them meaningful. The OM field provides rich contexts that help us to study important and relevant microlevel people issues and promote foundational understandings of behavioral concepts. For example, experiments that apply field contexts help us to establish a systematic body of knowledge on when behavior influences critical operational decisions. As a result, we can go far beyond studying behavior in simple settings, such as the ultimatum game.[2] Second, historically, as a society, we have worked with various forms of quantitative methodologies to study relevant and important operations management problems. Studying and quantifying the impact of behavior on operating systems truly require one to effectively master and use multiple methods (for example, mathematical, empirical, and experimental ones). We have done it before and are well positioned to continue to do so. Third, every science (for example, biology and chemistry) has an experimental component to observe and validate theories. Why not management science? It is a complementary and necessary approach to make the science real. In addition, organizations increasingly experiment, collect, and process enormous amounts of data regarding individuals' actions/decisions in a variety of operational contexts. The recent emergence of business analytics and data sciences has also made companies more open and willing to share such data with scholars who can help quantify the role of behavior in operations. Therefore, research in behavioral operations is even more necessary and exciting, and now, it is a fundamental and integral part of scholarly pursuit in manufacturing and service operations management.

We are excited about the opportunities that lay ahead for behavioral operations as scholars continue to explore new problem domains and broaden their research goals. We are confident that *M&SOM* will continue to play an important role in encouraging behavioral work and maintaining rigorous norms. Clear ethical norms are particularly important for experimental and field research, because investigations involving human participants can put people at risk. As the behavioral community expands into new data-rich investigations and more field-based experimentation, we will continue to look to *M&SOM* as the standard for ethical behavior. We trust that *M&SOM* will take on these challenges, balancing the pursuit of knowledge with care for the safety and wellbeing of the managers, workers, and customers that we strive to understand.

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Endnotes

[1] An insightful *M&SOM* blog entry by Gary Bolton and Elena Katok on September 16, 2015, helped disentangle the impact of these findings for the *M&SOM* community and the role of replication studies in fostering rigorous behavioral research.

[2] Behavioral economists, such as Camerer (2003), also called for a moratorium on creating more ultimatum-type game data and "shift [ing] attention toward new games and new theories" (Camerer 2003, pp. 115–117). We agree and encourage management scientist to leave behind those overstudied games and embrace and leverage the richness of their research contexts to bring in new insights for behavioral issues arising in manufacturing and service operations.

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