
Behavioral Operations Management

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Behavioral Operations Management

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Abstract

Behavioral Operations Management investigates new developments around behavioral components — “people issues” — in operations management (OM). While these “people issues” are not new, OM has not dealt with them in a serious or consistent manner until the last 10 years or so. What is new is the emergence of a set of methods and structured areas of study that allow researchers to study these issues *within* the OM paradigm. The authors provide a definition of Behavioral OM and survey a number of relevant behavioral issues and their applications to the existing OM research. Finally, the authors propose that culture studies in OM may represent a promising direction of future behavioral OM research.

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1

Introduction

The field of Operations Management (OM) “encompasses the design and management of the transformation processes in manufacturing and service organizations that create value for society. (...) the search for rigorous laws governing the behaviors of physical systems and organizations” [46, p. 8]. This is a broad definition, which leaves open the study of many relevant characteristics of these physical and organizational systems. A broad view is appropriate, especially as the editors of the “Operations and Supply Chain” department of *Management Science* emphasize the “editorial philosophy to focus on senior management issues” (*ibid*, p. 12). The above definition emphasizes the use of “normative mathematical models,” as opposed to “positive empirical findings in, e.g., the field of Organizational Behavior (OB)” (*ibid*, p. 13).

And yet, in the process of applying OM methods in managerial practice, members of the field have been left with disappointment and frustration. In the mid-1990s, a well-known Operations Research (OR) scholar remarked to one of the authors, “Of course, everyone knows that people in organizations apply our methods only half of the time; the other 50% of what they do is human foibles.” Although the OM

2 Introduction

field has always acknowledged social considerations in principle, it has shunned them *de facto*. This has led to calls for more emphasis on “human foibles” in academic literature: “Many of our techniques and theories ignore important characteristics of real systems and therefore are perceived to be difficult to apply in practice. A common factor in this breakdown is people. When it comes to implementation, the success of operations management tools and techniques, and the accuracy of its theories, relies heavily on our understanding of human behavior” [17, p. 737].

Thus, the burst of activity since about the year 2000 on *Behavioral Operations Management* stems from a long observed gap in OM, “people issues” in a wide sense, coupled with the emergence of a set of methods that promise the potential of being able to address such people issues. The recognition of this gap is not new, nor does it represent a “revolution” of the field. The field of OM has been aware of the relevance of people issues, and “danced around them,” ever since the 1950s. What is perhaps new is the emergence of a set of methods, and structured areas of study, that may allow us to study people issues *within* the OM paradigm.

Another anecdote is helpful to illustrate this: Around the year 2000, one of the authors discussed a behavioral issue with a colleague from OB. The colleague remarked, “My friend, if you continue this work, you’ll end up no longer an OM professor, but an OB professor! Want to join our department?” The answer to this teasing challenge is no, the purpose of Behavioral Operations is not to join the field of OB, its intellectual heritage and set of positivistic empirical methods. There is clearly an overlap in the phenomena studied, but the promise of Behavioral Operations is a continuation of using rigorous mathematical theory and scientific experimental methods to study a set of phenomena that were perceived as too unstructured to be amenable to being captured in models.

To emphasize the continuity of Behavioral Operations with OM, we start with a short overview of the field of OM. Then, we attempt a definition of Behavioral OM, and overview a number of important relevant behavioral issues and their applications in the existing OM

work. Finally, we propose that culture studies in OM may represent a promising direction of future behavioral OM research.

1.1 A Short History of the Discipline of OM

“It is difficult to pinpoint the origins of our field” [46, p. 8]. Its origins certainly go a long way back; some people trace them to Adam Smith’s *The Wealth of Nations* [204], where he demonstrated division of labor and productivity with his original pin-making example. Adam Smith’s seminal work led to Charles Babbage’s *On the Economy of Machinery and Manufactures* (1832), which “catalogued a vast wealth of operational details . . . a series of general principles . . .” [139]. Many current OM themes, such as planning and control, manufacturing policy, or process technology, have easily identifiable antecedents in Babbage’s book. However, applying scientific approaches to OM did not come into existence until the emergence of Frederick W. Taylor’s highly influential ideas and techniques embodied in his term “scientific management” [115].

One essential element of Taylor’s philosophy was “that scientific laws govern how much a worker could produce per day and that it is the responsibility of management (and staff) to discover and use these laws in carrying out production” [43], where “scientific” meant “based on proven fact (e.g., research and experimentation) rather than on tradition, rule of thumb, guesswork, precedent, personal opinion, or hearsay” [148]. During the early 20th century, Taylor and other pioneers inspired (such as Harrington Emerson, Henry Gantt, and Frank and Lillian Gilbreth) “fostered quantification of management” [106]. This included some early attempts of optimization, for example, in Harris’ EOQ model [98].

However, scientific management did not make the step to causal model-based theory. By the mid 20th century, the OM field was generally considered purely descriptive and synonymous with industrial management or factory management [33, 43, 159]. As other functional disciplines that had been considered part of industrial management (finance, marketing, and personnel management) gradually found ways of differentiating themselves and building their own methods and

identities, what was left over for OM was “a nearly empty basket of techniques: time and motion study, plant layout, Gantt’s production control boards, the simple EOQ model, and simplistic descriptions of how a production system worked” [33].

Meanwhile, in the 1940s and 1950s, the discipline of OR emerged from World War II and was extensively developed. Mathematical OR techniques were well-suited to the quantitative nature of OM problems and “provided the scientific methodology that allowed us to develop something akin to the ‘nature science’ or physics of operating systems;” the introduction of these techniques “rescued the field from extinction” [33].

The 1960s and 1970s were hallmarked as the “golden age” of Operations Research/Management Science (OR/MS) with highly influential applications in management, especially in OM [157]. Significant progress was made in the understanding of operations problems such as scheduling, planning, and inventory control. The dominant approach was to structure the problems as system optimizations with a single objective subject to a set of constraints.

The high dependence of OM on OR finally resulted in an “identity crisis” in the 1970s, that is, the definition of the field was challenged. A key reason was that research was narrowly defined relative to management’s scope, making the more sophisticated quantitative models difficult for managers to understand, and so they failed to follow the evolution of business practices; models became mathematically more sophisticated, exploring mathematically challenging problems rather than providing pragmatic answers to support real-world decision-making. An additional problem was that some OR/MS application areas successfully moved into other functional fields, such as accounting, finance, and marketing, and were no longer considered as OM [6, 33, 46].

Since the late 1970s, modern production and quality systems and philosophies, such as material requirements planning (MRP), total quality management (TQM), and the Toyota production system, particularly just-in-time production (JIT), have been introduced into industries. The ascendancy of these systems not only had a significant impact on business practice, but also “suggested that the locus of

creativity had shifted away from academia” [46, p. 9]. These industry-driven developments prompted OM to approach practice again, trying to explain why, and when, different practices worked. In the early 1980s, the discipline of OM was finally “emerging from the OR/MS phase into a clear recognition of OM as a functional field of management. . . . the field is a managerial one” [33]. The research focus increasingly shifted toward practical management concerns, and the importance of managerial implications of OM research was recognized more widely. OR/MS methodologies remained as predominant research tool kits in the field. However, the tactical issues examined by OR/MS started to become building blocks for higher level system-wide problems. In the same direction, operations strategy (earlier known as manufacturing strategy, [202, 203]) became a recognized subfield of OM: operations should not only reactively implement corporate strategy, but should also be actively involved in developing corporate strategy.

In the same trend of moving from tactical implementation problems toward higher-level managerial problems, OM experienced another expansion into a new sub-field in the early 1990s: as businesses evolved from centralized to more decentralized and partner-oriented organizational forms, game-theoretic models of decentralized decision-making and strategic interaction became prominent. An entire sub-area began to focus on supply chain coordination contracts that align local incentives of upstream and downstream parties [46, p. 10].

It is not surprising that an extrapolation of these trends of the field [46, p. 13] led to the prediction of an increasing emphasis on strategic issues (supply chain coordination and operations strategy) and intensifying interfaces and collaborations with other disciplines: Finance, Marketing, Services, R&D, and Organizational Behavior/Human Resource Management (OB/HRM).

The interdisciplinary collaboration with OB, which relates to the “people issues” that are mentioned in the opening paragraphs, is of course intimately related to Behavioral Operations Management. Expanding OM’s scope in the direction of people issues is clearly important, worth devoting an entire monograph to, and promising for highly relevant future work. However, this section should make one thing clear: Behavioral Operations Management is not the only promising

expansion of the OM field, it is not a new idea that OM should look at people issues (see, for example, [99, p. 242]), and it will not turn the fundamental premises of the field upside down. It is one of several interesting avenues of expansion.

We conclude this section with one more anecdote: in 1996, the Nobel laureate economist, Gary Becker, was asked about the weakness of economics in acknowledging the psychological roots and complications of decision-making. He replied, “Obviously, economics as a field has neglected psychology, and this needs to change. However, this does not mean throwing out of the window the premises of neoclassical economics; it provides a powerful paradigm of analysis which will be able to incorporate the additional considerations of the psychological system and provide stronger results.” The same holds for OM.

1.2 Behavioral Economics and Behavioral Operations

OM and OB studies have been progressing independently for a long period of time, with distinct research questions and methodologies and little interaction, although in real-world management OM and OB are fundamentally intertwined (as every practicing manager knows): “OM policies can only be carried out by people, and OB/HRM policies are effective if they foster people doing organizational-critical tasks” [27]. Consistent with the trends identified in Section 1.1, Boudreau et al. suggest that both OM and HRM studies can be better informed and greatly enriched by incorporating behavioral principles from HRM and operational principles from OM, respectively, and great research opportunities lie in an integrated OM/HRM area.

Until just a few years ago, human behavior had not received as much attention as the connection to other functional fields:

...the research in our discipline has remained largely disjointed from the social sciences literature on human resource management and organizational behavior (OB)... Operations management models have historically invoked oversimplified models of motivation, learning, creativity, and other such aspects of human behavior that are vital to the success of management

policies in practice. Models that can maintain high levels of rigor while incorporating these elements will be richer and more realistic [46, p. 13].

Around the turn of the century, this began to change — human behavior started attracting the attention of OM researchers. Several conferences on behavioral research in OM were held at Harvard and Penn State Universities, special issues appeared on behavioral topics in the OM journals *Decision Sciences* (DS), *Journal of Operations Management* (JOM) and *Manufacturing and Service Operations Management* (MSOM). A new editorial department of Behavioral Operations has been established in the journal *Production and Operations Management* (POM), and the pipeline of research on behavioral operations management is growing fast (discussed in the next section). “Behavioral Operations Management” (Behavioral OM) has become something of a buzzword capturing a potentially emerging field. However, no consensus has (yet) been reached on defining the field; for example, it is not clear what scope the term “behavioral” should denote.

Bendoly et al. [17, p. 3] emphasize people issues (as the opening quote shows), but see behavioral OM, following experimental economics, as focused on experimental studies: “The experimental economics field has seen exponential growth every decade since 1960. Through this evolution, the focus of experiments has expanded to include an emphasis on developing new behavioral theory to explain gaps between established economic theory and experimental results.”

The equation of Behavioral OM with experiments seems narrower than the spirit of the attempt to expand OM to incorporate people issues. A broader definition is offered by Gino and Pisano [86]: “*the study of attributes of human behavior and cognition that impact the design, management, and improvement of operating systems, and of the interaction between such attributes and operating systems and process.*”

The pitting of “experimental” versus “behavioral” is not new and reflects a similar conflict in economics. For example, in 2002, Daniel Kahneman co-received the Nobel Prize in Economic Sciences for “for having integrated insights from psychological research into economic science, especially concerning human judgment and decision-making

under uncertainty” (behavioral), while Vernon Smith co-received it for “having established laboratory experiments as a tool in empirical economic analysis, especially in the study of alternative market mechanisms” (experimental).¹

We believe that, in line with Chopra et al.’s broad definition of OM, we should not restrict Behavioral OM to one methodological approach, we should strive for both modeling (theory) and empirical methods (experimental and others). Both are necessary for the successful development of the field (discussed in Section 1.4). While experimental economics has established laboratory methods in studying human behavior and economic theories, behavioral economics attempts to incorporate psychological considerations into the neo-classic economics paradigm:

Because economics is the science of how resources are allocated by individuals and by collective institutions like firms and markets, the psychology of individual behavior should underlie and inform economics. However, economists routinely — and proudly — use models that are grossly inconsistent with findings from psychology. A recent approach, “behavioral economics,” seeks to use psychology to inform economics, while maintaining the emphases emphasis on mathematical structure and explanation of field data that distinguish economics from other social sciences. In fact, behavioral economics represents a reunification of psychology and economics, rather than a brand new synthesis, because early thinking about economics was shot through with psychological insight. For example, in his *Theory of Moral Sentiments*, Adam Smith described all the ways in which people care about the interests of others [36, p. 10575].

Camerer’s explanation of why psychology and economics evolved separately from each other during the 20th century is instructive: “Economists worked hard at formalizing economics mathematically,

¹ See <http://nobelprize.org/nobel.prizes/economics/laureates/2002/>.

with physics as inspiration. Psychologists were also inspired by natural sciences — by experimental traditions rather than mathematical structure. As a result, to an economist, a theory is a body of mathematical tools and theorems. To a psychologist, a theory is a verbal construct or theme that organizes experimental regularity” (p. 10575).

Behavioral economics challenges and relaxes the neoclassical assumption that people are self-interested rational agents with stable preferences. The “conviction is that increasing the realism of psychological underpinnings of economic analysis will improve economics on its own terms — generating theoretical insights, making better predictions of field phenomena, and suggesting better policy” [37]. Several psychological observations of individual behavior have fundamentally questioned mainstream economic models and, more importantly, provided useful suggestions for modifications of the traditional economic framework, even without inventing methodologies beyond the scope of mainstream economic analysis [181, 182]. Already over the last few decades, behavioral economics has become influential in other fields, such as Marketing and Finance, which leaves OM as perhaps the last field of management studies to embrace behavioral issues.

Although OM has always acknowledged the importance of people in principle, most OM researchers would agree that this has remained lip service — the field has been heavily reliant on oversimplified assumptions essentially requiring that people be deterministic, predictable, and emotionless [27]. Indeed, most OM studies implicitly assume that people can be integrated into manufacturing or service systems like machines. Even when strategic interactions were incorporated into the field in the early 1990s, the core assumptions of neoclassical economics were used: decision-makers act solely to optimize measures of discounted future wealth. In the case of strategic interactions, decision-makers choose their responses to other parties’ actions in the same way, driven by discounted future payoffs. Evidence has mounted that a view of man as an aloof trader is distorted in many, if not most, cases [70].

Camerer’s diagnosis of incompleteness of economics and both its complementarity with and separatedness from psychology closely

parallels the history of OM and OB [36]. Camerer’s definition holds useful insights for a conceptualization of behavioral OM that complements and broadens the definitions above. Camerer even provided additional mathematical structures for how insights from psychology might be translated into parsimonious modifications of economic utilities:

1. Reference-point-dependent utility (prospect theory) and loss aversion extend expected utility. People evaluate payoffs from the *status quo* and view gains differently from losses.
2. Hyperbolic discounting, or a preference for immediacy, extends consistent exponential discounting. People react more strongly to salient and immediate events than to events in the future, thus causing time reversal of preference inconsistencies and myopic behavior.
3. The consideration of equilibria in the theory of strategic interaction (game theory) is extended by transient analysis, informed by reinforcement learning (simple rules of updating information rather than full Bayesian updating).
4. Social utility, or the consideration of the effect of one’s actions on others, extends self-interested payoff maximization.

In other words, Camerer proposes that the key extension of neoclassical behavior lies in systematic individual “decision biases,” or deviations from normative decision theory (in particular, loss aversion and immediacy) and in social preferences that prompt people to intrinsically care about what happens to other people (independent of effects on the self); in addition, the path of a group toward equilibrium matters, not only the equilibrium itself (which may never be reached). Note that these extensions represent important extensions of the definitions by Bendoly et al. [17] and by Gino and Pisano [86], both of which focus on individual decision biases (not social utility), and the first two definitions are also restricted to empirical or experimental work rather than on the combination of data with mathematical theory. With these insights, we can now attempt to propose a definition of behavioral operations.

1.3 Behavioral Operations: An Attempt of a Definition

We have seen that some approaches to the emerging field of Behavioral Operations stress an “experimental” emphasis, proposing, “let’s add experimental investigations to our OM models to see whether they are realistic.” This seems insufficient — it should be no more than good scientific practice to attempt empirical tests of mathematical theory, and it falls squarely within the broad definition of OM, as laid out by Chopra et al. [46].

Several definitions emphasize the “individual decision biases” extension of OM [17, 86]. However, when we recall that the purpose of behavioral operations is to “bring people issues back into the discipline” and provide an interface to Organizational Behavior and Human Resource Management, we should encompass *both* individual decision psychology (and the associated deviations from normative decision theory) and the influence of group dynamics, emotions, and culture on interactions among actors in processes.

The efforts of reunifying psychology and economics [36, 181, 182] give us a good start to define behavioral operations. However, we need to first find appropriate application areas for behavioral studies in OM, and then acknowledge that the vision of “bringing people issues into OM” requires including not only human psychology, but also human culture.

Let’s first recall that OM is about the “design and management of the transformation processes in manufacturing and service organizations that create value for society” [46], and therefore requires more operational and actionable studies (just as OM models have always been detail-rich than economics models). Second, human behavior that goes beyond maximizing payoffs can be classified into three different categories: individual decision biases due to cognitive limitations, individual other-regarding behaviors in the context of social interactions driven by social goals that are rooted in psychology, and finally collective behaviors in a population as an outcome of culture transmission and evolution. All three behavior categories have been examined with mathematical models as well as experimental studies.

The first category of OM-relevant behavior has been studied in literature on heuristics and biases in judgment and decision-making. People deviate from normative decision theory not only because they are loss-averse and like immediacy (overly discount the future), but also because they are boundedly rational (they overlook information when they are occupied, they intuitively linearize complex causal connections and extrapolate even when it is not justified), they are overconfident (overestimate their ability of control in areas in which they feel confident, and underestimate intervals of decision outcomes), they shun ambiguity (unknown outcomes with unknown probabilities) and complexity, and they are easily anchored and conformist (their estimates are biased by previous information and by peer pressure).

The second behavior category is concerned with social interactions in OM. The social utility aspect of behavioral operations reflects not only psychology, but even more importantly, social psychology, evolutionary psychology, and anthropology. Social preferences have a clear structure that helps people to intuitively navigate the complexities of social interactions based on emotional “heuristic” cues: people everywhere intrinsically value status and respect, relationships, fairness in the relationships, and identify with a group that possesses a positive image. We will overview the work that has established these social preferences in Section 3; we can already state here that these preferences have a great impact on the performance and motivation of workers in the context of an operational process. The social preferences are, in our opinion, an even more important part of behavioral operations than cognitive biases — any operations manager who fails to be aware that people do *not* care only for incentives and payoffs, and that they deeply care about other aspects of social interactions as well, will not succeed as a manager.

A third area that we think needs to be incorporated in the new behavioral operations field in the future is culture, the knowledge and skills that are acquired and transmitted through individual learning and social learning in a given population. Culture consists of rules that reflect the experience of a group over time, and has been “automated,” accepted without question by the group’s members. Clearly, cultural assumptions are relevant for decisions in operational processes. Culture

has been “off limits” for operations management in the past, partially because it is so difficult to make operational. However, it turns out that mathematical theories of culture have been developed in anthropology and sociology [28, 29, 156] that are amenable to OM-style models and empirical tests of process design and performance. This research area clearly represents an overlap with the field of OB. But that is precisely what “interfaces” between disciplines are about: the possibility of studying OB “territory” with OM-style mathematical theory and empirics or experiments, offers an opportunity of complementarities with OB researchers and exciting new insights. We will discuss this further in the last section.

In summary, we finally arrive at our proposal of a definition of Behavioral Operations Management.

OM is concerned with the study of the design and management of transformation processes in manufacturing and service organizations, building mathematical theory of the phenomena of interest and testing the theory with field data (derived from surveys, databases, experiments, comparative case studies, ethnographic observations, etc.). Behavioral Operations Management is a multi-disciplinary branch of OM that explicitly considers the effects of human behavior in process performance, influenced by cognitive biases, social preferences, and cultural norms.

1.4 On the Complementary Roles of Modeling and Experiments

We have already alluded to the debate between advocates of experiments and empirical work, and modelers. As one member of the “empirical camp” commented, “the emergence of behavioral operations should not be viewed as an opportunity to further complicate ‘toy models,’ but rather an opportunity to truly reflect upon some of the long held assumptions on which much of operations research models have been founded, and move forward from there. I don’t see real progress taking place in this area if a predominance of modelers jumping on the

behavioral operations bandwagon are averse to conducting real-world observations of behavior.” In this section, we argue for a *combination* of theory and empirical approaches, only the combination adds up to science.

In a 1995 study, Thomas Powell empirically examined whether TQM methods represented a strategic resource of the firm [178]. He found that of 12 TQM factors, the 9 formal process ones (adoption and communication of TQM, customer relationships, supplier relationships, benchmarking, training, zero-defects mentality, flexible manufacturing, process improvement, and measurement) were not significantly associated with company performance, while the three “intangible” factors of committed leadership, open organization and employee empowerment, were significant performance drivers. Powell concluded that “rather than merely imitating TQM procedures, firms should focus their efforts on creating a culture within which these procedures can thrive. (...) Perhaps TQM’s highest purpose, and its real contribution to American business, is in providing a framework that helps firms understand and acquire these resources as part of an integrated change program” [178, pp. 29 and 31].

This study holds lessons for OM scholars on two dimensions. First, it is part of mounting evidence that formal processes and optimization of explicit goals, the traditional domains of OM, are insufficient to explain organizational success. Complaints have long accumulated that formal methods have had unsatisfactory impact in practice (e.g., [49, 146], but the field of OM largely ignored the explanatory gap until recently. The emerging sub-field of Behavioral OM is precisely about identifying additional factors (besides optimization and incentives) that influence behavior, such as decision biases, emotions, and culture, which constitute the main focus of this article.

Second, Powell’s study demonstrates the limits of empirical research. The study’s results point to “intangible” factors, which replaces one mystery (the insufficiency of formal methods) with another — why would an “open” non-hierarchical organization, management commitment and empowerment explain the success of TQM methods better than the processes? Is it because empowered decision-making brings better information (at the front line) to bear? Is it

because committed management is more flexible in dealing with uncertainty? If the reasons are really better decision-making, why is that “intangible” and not measurable as part of the processes? If the “culture” leads to more motivated employees who try harder, why can one not measure and incentivize how hard employees try?

The problem lies not in the empirical (or experimental) approach *per se* — the need for empirical testing of theory is plain and clear for all to see. The problem lies in the fact that in the social sciences, empirical work is predominantly based on verbal theory, or the qualitative description of phenomena with prose. As the term “behavioral” in Behavioral OM seems to be often seen as synonymous with “experimental,” which almost looks like an “anti-modeling” stance, we must discuss this limitation in some more detail.

Verbal theory is limited simply because it is incapable of precisely describing complex systems — emergent system-level phenomena that require descriptions of the system elements as well as of interactions require description with symbols. Prose simply cannot “keep all the balls in the air” to allow sufficient precision; only mathematical characterizations can quantitatively describe system behavior. Without quantitative description, we cannot measure and achieve progress.

In the words of Richerson and Boyd [185, p. 248], “models of modestly general applicability and empirical generalizations of modest scope are extremely valuable for two reasons. First, individuals are quite stupid compared to the complexity of the problems we aspire to solve. An isolated individual thinker has no chance against a problem of any complexity. Well-studied models and well-tested empirical generalizations embody the collective of one’s fellow scientists. (...) Second, most concrete cases are so complex that no one investigator can hope to study in detail every dimension of the problem; it is necessarily simplified, often drastically. (...) Theories help to make this simplification transparent.”

“When used properly, mathematics schools our intuition in ways no other technique can. (...) Good models produce diamond-clear deductive insights into the logic of evolutionary processes [and complex systems, more generally]. (...) When it comes to subject areas like evolution [or complex systems, more generally], one cannot think

straight without them. You don't have to be a modeler to appreciate models. Much like in any other art form, educated connoisseurs can get a lot out of them. However, in the end, data are the ultimate arbiter." [185, pp. 256–257].

The large conceptual breakthroughs in theoretical biology on the question of altruism (rather than raw selfishness) of animals, starting from the 1960s, were made with simple conceptual models, to name a few important ones: [95] (altruism for relatives) and [96] (group selection), [224] (reciprocal altruism), and recent models on the safeguarding of cooperation in groups through punishment [167], and finally, Boyd and Richerson's methods of modeling cultural evolution have been extended to explain many empirically observed aspects of culture [28]. The same holds in Behavioral OM: well chosen collections of simple models of decision biases as well as social preferences hold the promise of sharpening the experimental work [25, 42, 73, 108, 180, 197].

Simple models of partial phenomena that are modular and sufficiently significant to explain important aspects of real phenomena (not to be confused with "reality") can then be used to put more complex system, after the components have been understood, and to test specific implications quantitatively with more precision than verbal theory allows.

In light of its fast growth in the last few years, we are convinced that behavioral OM will bring tremendous research opportunities for OM. OM is a field that is familiar with mathematical models and understands their use, both as simple models and as "complete" decision support models in well-understood situations with ample data availability. Thus, it seems surprising that there is even any discussion about Behavioral OM shunning modeling. With appropriate extensions of traditional rational choice and game theory models to incorporate decision biases, emotional or social preferences, and cultural norms, mathematical models can guide empirical testing in behavioral OM just as well as in OM at large.

First, math models will produce OM theories and hypotheses for experimental studies. Many traditional OM problems have been well structured and analyzed in mathematical models, for example, the

newsvendor problem, the bullwhip effect, and supply chain contracting and coordination, all of which have elegant models that have been experimentally tested. The models provide not only testable hypotheses, but also simplified system structures that can be easily recreated in the corresponding experiment designs. Attesting the need for behavioral OM as an expansion of the field, empirical tests have clearly shown that the traditional OM models are incomplete.

By now, a sufficient number of models has been published which show that models of operations problems can be extended to include decision biases, emotions and social preferences, and cultural norms. Mathematical models of fundamental human behaviors ranging from individual level to population were first developed in other fields, such as economics and sociology. For example, reference-dependence and time-preference have been formally modeled to capture the empirical regularities that individual's preference can be reversed by reference point and time, respectively. Social preference models capture that human behavior can be biased by social interactions, and that people have a concern for others in addition to being self-interested. Finally, cultural evolution models are used to study how social behaviors evolve and are transmitted in a population. The modeling techniques are well established and similar to methods already used in OM, and thus readily adaptable.

The ability of models to analyze behavior of complex systems is highly relevant for behavioral OM — most modern OM problems involve complex decision-making in decentralized systems, and they can quickly become too hard to study without the help of models. There are simply too many interacting variables to control. Once the models have produced predictions of emergent system behavior, we can go back to experiments, or empirical studies, with a few controls. Of course, the arbiter is data — we are not proposing that behavioral OM should only be model driven; it should be model driven and experimental or empirical. Models can guide experiments to test emergent behavior that cannot be predicted otherwise.

2

Individual Decision-Making Biases

Behavioral OM represents the interface of OM with the social sciences, in particular OB, decision science, and psychology. Thus, there is a huge treasure of studies and insights available on human behavior, which can be incorporated in understanding employee performance in operational processes.

In contrast to the normative research, which is widespread in economics and OM, and examines “what a decision-maker should rationally do,” research in decision science and psychology is primarily descriptive and focuses on explaining “how real decisions are made.” Indeed, a wide gap between experimental findings on decision-making and normative decision theory has been found. The behavioral principles discovered from descriptive research on decision-making are of great importance to OM, in particular when it is evident that the normative models based on hyper-rationality assumptions, which are popular in OM research, may not help much in the complex reality.

Under the hyper-rationality assumption, decision-making requires unlimited cognition and computation capability to identify all the alternatives, determine all eventual consequences of each alternative, and select the best according to the decision-makers’ preference [200].

However, in many complex and uncertain situations, people fail to make such rational decisions, and instead, undertake only limited search and make *satisficing* rather than optimal decisions. This is because people have only limited capability of formulating and solving complex problems (due to limited cognitive capacity, lack of information, and time and cost constraints), are only partly or boundedly rational, and they may sometimes even be irrational or emotional [200, 201].

However, dismissing emotional behavior as “irrational” is misleading. Psychologists have provided strong evidence that emotions guide actions in situations of imperfect knowledge and multiple, conflicting goals (bounded rationality); they make available repertoires of actions that have previously been useful in similar circumstances [56, 163, 195]. In other words, emotions form the basis of our “rational” intelligence; they do not contradict it (see also Section 3).

In addition to the concept of bounded rationality, detailed studies of human decision-making processes in psychology continue to clarify the human mental structures involved in decision-making. This section overviews some important findings in these fields and then discusses their relevance to OM, particularly process design. As we will see in the rest of this section, the findings cannot only provide illuminating inputs into OM models, but can also help develop more realistic decision criteria, or objective functions, for mathematical models.

2.1 Reference Dependence and Prospect Theory

2.1.1 Foundations

Expected utility theory plays a central role in standard economic analysis. It assumes that the decision-maker maximizes the expected utility of the final state of his wealth. This theory and its applications rely on a small number of assumptions about human behavior (formally called axioms). However, experimental studies on decision-making under uncertainty have shown that people, when asked to make real decisions, often violate the expected utility theory axioms (for example, the Allais paradox represents a classic counterexample to the independence axiom of expected utility theory). Therefore, the explanatory power of expected utility theory is limited.

As the first attempt to develop alternative theories to overcome the limitations of expected utility theory, prospect theory proposes that preferences are defined by the *deviation from a reference point* rather than by the final state of the outcome: positive deviations are coded as gains and negative deviations as losses [114]. Thus, the value function (in prospect theory, “value” takes the place of “utility”) depends on a reference point and is expressed mathematically by a kinked S-shaped function. This value function is concave in the gains domain, reflecting risk aversion, and convex in the loss domain, reflecting risk-seeking behavior (Figure 2.1). People exhibit “loss aversion,” that is, losses result in larger disutility than the value derived from the same size of gains: for example, losing \$50 causes more pain than gaining \$50 produces pleasure.

Two cognitive biases, the *endowment effect* and the *status quo bias*, are closely related to prospect theory and its associated loss aversion [113]. The former refers to the fact that people place a higher value on an object once they possess it than before they gained possession [221]. The latter refers to the situations when people exhibit a preference for the *status quo* over alternatives that are attractive but may force a change [124].

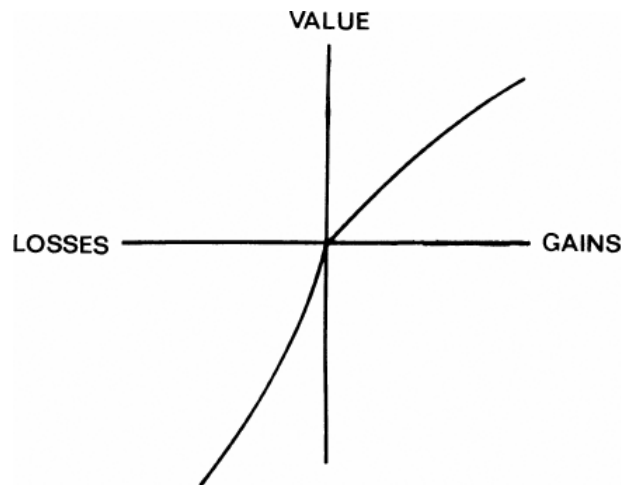


Fig. 2.1 A hypothetical value function in Prospect Theory [114].

However, it seems premature to believe that our collective understanding of these cognitive biases is complete. Some new work has re-examined the endowment effect using new methods aimed at more thoroughly excluding subject misconceptions [174, 175]. This study finds the gap between willingness-to-pay and willing-to-accept can be “turned on and off” depending on the experimental procedures; thus, the study puts into question the gap as supportive evidence for the endowment effect. This implies that we must collect further evidence on this bias.

Another important element of prospect theory is the idea that people have decision weights rather than probabilities when evaluating risky choices. The decision weight transforms the probability of outcomes in a nonlinear manner, i.e., overweighting small probabilities and underweighting medium probabilities. Such a nonlinear transformation of probabilities is not unique to prospect theory; there are analogous extensions of expected utility theory. For example, in the context of subjectively weighted utility (SWU), Karmarkar developed a descriptive model of transforming probabilities into subjective weights with a specific functional form, in a way that is consistent with prospect theory [116, 117].

The essential principles of prospect theory, reference dependence and loss aversion, have been acknowledged in formal economics models. Köszegi and Rabin developed a general model that includes both final outcome utility and “gain–loss” utility in the following form [128]:

$$u(x|r) = m(x) + n(x|r),$$

where $u(x|r)$ is the overall utility as a function of the final outcome x and reference point r , $m(x)$ is the utility derived from the final outcome, and $n(x|r)$ is the gain–loss utility defined over gains and losses depending on the reference point. In prospect theory, the value function is defined solely based on the changes in the final outcome utility in the form of $v(x - r)$, whereas in the gain–loss utility of Köszegi and Rabin, $n(x|r)$ is defined by the changes in the final outcome utility, and thus $n(c|r) = \mu(m(c) - m(r))$. Loss aversion in this model is captured by explicitly defining the properties of the gain–loss utility function, e.g., the utility function on the losses domain is steeper than on the

gains domain and kinked at 0 such that $\mu'_+(0) < \mu'_-(0)$. Moreover, this utility can be defined in multiple dimensions provided that the utility function is additive over dimensions.

Kobberling and Wakker constructed the reference dependent utility by explicitly introducing an index of loss aversion [126]. Their model assumes a basic utility function of outcome $u(y)$ defined in terms of gains and losses and λ as the index of loss aversion in the following form:

$$U(y) = \begin{cases} u(y) & \text{if } y \geq 0 \\ \lambda u(y) & \text{if } y < 0. \end{cases}$$

Here, the basic utility function $u(y)$ is smooth at 0, and thus the kink of $U(y)$ at 0 is caused by loss aversion, a psychological factor that exists separately from outcome utility.

2.1.2 Applications in OM

Prospect theory describes a common mental process of how people actually make choices when facing risk and uncertainty, as well as a relatively simple mathematical basis for modeling utility functions for economics analysis. The modeling approach and analysis of reference-dependence and loss aversion are applicable to OM studies.

In many OM models, decision-makers are assumed to be risk-neutral and loss-neutral and, moreover, to maximize profit (or the expected profit in an uncertain environment, which allows them to act as if there was one final outcome). However, as the rationality assumption seems unrealistically restrictive and contradicting recent empirical research, two general issues deserve further investigation. First, how do optimal decisions change when decision-makers indeed have reference-dependent preferences and are loss averse (as opposed to having “absolute” reference-independent preferences). As we discussed above, mathematical models of reference-dependent utility can capture such behavior and, at the same time, maintain analytical tractability. Schweitzer and Cachon develop a newsvendor model with loss aversion but fail to find experimental support for loss aversion [197]. A loss-averse newsvendor model is further developed by Wang and Webster,

who analyze in greater detail how order decisions can be biased relative to the standard newsvendor model [236].

The second example here presents how loss-aversion models can explain “anomalies” in an empirical study of coordinating contracts [104]. The authors investigate the coordinating contracts in a buyer–seller dyad (two-part tariff and quantity discount contract) in laboratory experiments with human subjects, and find no support for the theoretical (“rational”) predictions. They further find that reference-dependence models of loss-averse buyers explain the empirical observations better. In this model, a buyer facing a two-part tariff contract frames the upfront payment as a loss (a negative change from the *status quo*) and frames the subsequent profit as a gain. Therefore, the buyer’s preference is modeled as a function of profit from the transaction and a “perceived” loss from the upfront payment in the contract design. The equilibrium behavior is biased by the loss aversion, a prediction that is supported by the empirical data from the laboratory experiment. This study clearly rejects the standard “rational” supply chain coordinating models.

The second issue with the standard hyper-rationality assumption is concerned with optimal decisions when the decision-maker himself or herself remains rational and seeks maximal profit, but reference-dependence and loss-aversion preference occur in the surrounding business environment. Clearly, the decision-maker should consider this in his/her decision problem. In contrast to describing how decisions are biased by loss aversion, the analysis in this case can be rather prescriptive, suggesting what a rational decision-maker should do. We summarize one example of such a situation in the context of revenue management and dynamic pricing: the firm wants to maximize profits, facing consumers who are “irrational” in the sense that their purchase decisions are influenced by past prices through reference price effects [177].

In this study, the rational firm wants to maximize long-term profit by choosing optimal inter-temporal pricing policy. The demand of a certain period t , D_t , is a function of not only the current price P_t but also the customers’ reference price R_t , which is formed based on past prices. The demand is modeled by following the spirit of prospect theory, that

is, customers' purchase decisions are made by assessing price P_t as well as gains ($P_t < R_t$) or losses ($P_t > R_t$) relative to the reference price R_t . The model allows demand D_t to depend on $(P_t - R_t)$ in the same manner as in prospect theory, such that losses loom larger than gains. The reference price R_t is updated by an exponential smoothing mechanism $R_{t+1} = aR_t + (1 - a)P_t$. Thus, the firm's current price affects future reference prices, which, in turn, influence customers' future purchase decisions and demand. The analysis suggests that, in order to attain the maximal long-term profit, the firm should price either constantly below or constantly above the reference price over time, until the prices converge to a constant price (the reference prices converge to this price at the same time). In other words, the reference prices associated with an optimal pricing strategy monotonically decrease or increase over time (the prices themselves are not necessarily monotonic). Under such a pricing strategy, customers continue to experience gains (or losses) over time.

These examples suggest that prospect theory offers the opportunity not only of extending OM research to more descriptive studies with more explanatory power, but also of enriching prescriptive models with greater realism. Although this comes at a price, as reference-dependent preferences complicate the problem formulation (in particular, the kink in the utility function may make the analysis harder), existing work shows that the resulting more realistic models can still remain tractable, and useful analysis can be done.

2.2 Immediacy, Salience, and Hyperbolic Discounting

2.2.1 Foundations

Time is an important dimension in decision-making, although time itself is not necessarily a decision variable. First, problems are often solved through a string of decisions made sequentially over time. Second, even when a decision is made at a single moment, the resulting costs and benefits might be realized at later points in time. These time-related complications can be circumvented by adopting a discounted utility framework, in which decisions are *time-independent*. This means that the same choice would be made if exactly the same

situation arose in the future. In discounted utility models, decision-makers are assumed to have an exponentially discounted utility, which implies that they trade-off inter-temporal costs and benefits by a constant discounting rate [191]. The discounted utility at time t has the form $U^t(u_t, u_{t+1}, \dots, u_T) = \sum_{\tau=t}^T \delta^\tau u_\tau$, where $0 \leq \delta \leq 1$ is the discount factor, and u_t is the instantaneous utility at time t . The discount rate δ remains constant over time. Discounted utility has been found to be violated in many studies; one of the most widely discussed violations is hyperbolic discounting.

The main characteristic of hyperbolic discounting is that the discount rate declines over time. George Ainslie was the first to connect “specious rewards” or “impulsiveness” to hyperbolic discounting [3], and to observe that it leads to *time reversal of preferences*, which constitutes a violation of “rationality” [80]. A simple and well-documented example of preference reversal is the following: people quite commonly prefer \$110 in 31 days to \$100 in 30 days, and at the same time prefer \$100 today to \$110 tomorrow. That is “irrational” because it means that I can influence your choice by shifting the decision backward and forward in time.

Hyperbolic discounting reflects a mental tendency to value “a bird in the hand” *much* higher than “two in the bush,” which reflects the complexity and ambiguity of the environment relative to our abilities of calculation and prediction. Thus, the difference between *now* and *any time in the future* is more important than the difference between *soon* and *later in the future* (leading to a decreasing discount rate) — events at both future times are ambiguous. The salience of immediate rewards can cause people to make “short-sighted” decisions that generate high immediate satisfaction but low long-term welfare. People tend to vastly undervalue future events. This is summarized by Camerer and Loewenstein [37]: “People will make relatively far-sighted decisions when planning in advance — when all costs and benefits will occur in the future — but will make relatively short-sighted decisions when some costs or benefits are immediate.” In other words, I can indeed influence your choice by manipulating immediacy, as certain financial products and the sweets at the supermarket checkout attest.

The most widely used mathematical model of hyperbolic discounting in economics literature is the (β, δ) preference, also called the quasi-hyperbolic discounting model, originally developed by Phelps and Pollak [171]. The model has two parameters (β, δ) to reflect the declining discount rate, and is mathematically expressed as follows:

$$U^t(u_t, u_{t+1}, \dots, u_T) = \delta^t u_t + \beta \sum_{\tau=t+1}^T \delta^\tau u_\tau,$$

where $0 < \beta, \delta \leq 1$. Compared with the exponential discounting model, $\beta < 1$ implies that the immediate utility has a higher impact on the overall utility. The hyperbolic discounting model has been used to study consumption saving, procrastination, and addiction in economics [133, 134, 164, 165, 166]. Based on the (β, δ) preference, a person can be classified as “naïve” if she is completely unaware of her time-inconsistency (and possible time-reversal of preference), as “sophisticated” if she is fully aware of it, and as “partially naïve” if her awareness lies in between the two extreme cases [166].

2.2.2 Applications in OM

Inter-temporal decision-making is also an important aspect of many OM problems. For example, in project management and new product development, critical decisions are made at sequential milestones over time, such as project scheduling and payment, or go/no-go decisions during product development. Widely used formal decision methods, such as dynamic programming, are based on the discounted utility framework with long-term profit maximization using a constant discount factor. The output of such a formal method is an “optimal state-contingent plan” that the decision-maker can follow all the way until the end of the planning horizon, behaving consistently throughout. The questions that arise are: Do decision-makers, in reality, follow such optimal plans, and do they execute what they have planned?

Empirical evidence suggests that the answer is no — decision-makers often do not follow their own plans, even without external forces (such as uncertainty) to derail them. As an example, it is well-known in project management that many projects are not completed within schedule and

budget. This phenomenon is called “planning fallacy” in psychology, referring to a systematic tendency to underestimate project duration. The following simple immediacy bias (hyperbolic discounting) model illustrates how plan and execution can become mismatched. Suppose a project requires an amount of work W to be finished within T periods, any delay costs P per unit time, and finishing earlier is rewarded by R per unit time. Each period, the agent must choose the amount of work, E_t , knowing that he will suffer a quadratic effort cost, E_t^2 . The agent’s period 1 decision is to minimize the remaining discounted cost by setting the immediate effort E_1 and planning for the future efforts $E_2, \dots, E_{T_1}$, with the plan foreseeing completion after period T_1 :

$$\begin{aligned} \min \quad & \delta E_1^2 + \delta\beta \left(\sum_{t=2}^{T_1} E_t^2 + P(T_1 - T)^+ - R(T - T_1)^+ \right) \\ \text{s.t.} \quad & \sum_{t=1}^{T_1} E_t = W. \end{aligned}$$

In each period, the decision-maker has the power to revise his plan for the remaining periods. The decision-maker has an immediacy bias: the immediate cost is more salient, and future costs are hyperbolically discounted. It is easy to solve the optimal plan for this model, not only the current plan but also the revised plans in all future periods ($E_2, E_3, \dots$). At the beginning of period 2, the decision-maker reconsiders his current effort and all future efforts. The cost salience makes his revised optimal effort level less than the one originally scheduled in period 1. In other words, the work that was planned in period 1 cannot be accomplished in period 2 because the cost in period 2 is more painful when it becomes immediate in period 2, as compared to the foresight during period 1, when the original plan was set. The same mismatch between plan and execution remains until the last period, which will, in this simple deterministic model, be delayed as opposed to the originally planned T_1 . The point here is that hyperbolic discounting provides a tractable explanation for delays, common in project management practice, even without any presence of project risks. Based on such models, we can design incentives that help project managers to overcome immediacy bias [165].

An increasing application area of hyperbolic discounting is in the area of dynamic pricing and revenue management, where it is crucial