Behavioral Operations and Supply Chain Management – A Review and Literature Mapping

Abstract

Behavioral operations research has proliferated greatly over the decade since its first formal review in 2006. The growth of the field warrants an objective mapping of contributions to the literature and the identification of trends. We conduct a systematic review of the literature of behavioral operations and supply chain management (BOSCM) across eight key operations and supply chain management journals, with publication dates through the end of June 2018. Collected articles are categorized into twelve operations contexts as well as emerging topic considerations. Key research trends, theoretical foundations and methodological choices are discussed in each context. The results show that supply chain management, inventory management, and procurement/auctions have been the most popular operations contexts for BOSCM researchers. The results of our co-citation analysis shows that the fundamental research areas that have informed and shaped the field include supply chain risk management, marketing, cognitive psychology and social psychology. Based on these findings and a survey of the most prolific authors in the field, we discuss possible avenues for future research.

1. Introduction

Behavioral operations is a promising and well-received emerging research domain within the field of operations management (OM). Most behavioral operations research concerns the effects of cognitive biases, personal and social preferences, and cultural norms on decision-making in operations and supply chain management (OSCM). During the past decade, research in this domain has attracted the attention of leading OM scholars and top-tier journals. A few special issues and discussion forums have been dedicated to behavioral operations-related topics; for example, the special issues of Journal of Operations Management (Bendoly et al., 2006; Croson et al., 2013), Manufacturing & Service Operations Management (Gans & Croson, 2008), and Journal of Supply Chain Management (Eckerd & Bendoly, 2011). Production and Operations Management Journal and Decision Sciences Journal have created departments for Behavioral Operations. A few books and handbooks have also been devoted to research advancements in this domain (e.g., Katok, 2011; Bendoly et al., 2015; Donohue et al., 2018). These efforts have inspired the broadening and maturation of this domain (Croson et al., 2013).
There have been some attempts to define the scope of behavioral operations research. Some of the broader and more popular definitions are as follows.

- Behavioral operations 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 (Loch & Wu, 2007).
- Behavioral operations research is the study of attributes of human behavior and cognition that impact the design, management, and improvement of operating systems, and the interaction between such attributes and operating systems and processes (Gino & Pisano, 2008).
- Behavioral operations is the study of potentially non-hyper-rational actors in operational contexts; at its simplest form it must have elements of both operations and behavior (Croson et al., 2013).
- Behavioral operations aims at understanding the decision-making of managers and using this understanding to generate interventions that improve supply chain operations (Katsikopoulos & Gigerenzer, 2013).

Most of these definitions consider the fact that behavioral operations research has expanded to also include multi-tier operations and the consequent challenges of inter- and intra-organizational decision making. This is the core of supply chain management (SCM). Therefore, we use the term Behavioral Operations and Supply Chain Management (BOSCM) to emphasize behavioral decision making in both intra-organizational OSCM domains (single and multi-tier). A study falls within the area of BOSCM if it is within the context of OM/SCM, it is behavioral in nature (i.e., focuses on deviation from rational key-performance optimization), and it concerns human behavior at a micro-level. We will further elaborate on this definition later in this paper.

Apart from the aforementioned special issues, several literature reviews of the behavioral operations context have been published during the last decade (e.g., Bendoly et al., 2006; Loch & Wu, 2007; Gino & Pisano, 2008; Größler et al., 2008; Bendoly et al., 2010; Knemeyer & Naylor, 2011). Table 1 summarizes the characteristics of a selective number of these reviews with high citation counts (i.e., type of classifications, OM areas, and journal coverage). Even though these papers are useful, they are not without limitations. First, except for Bendoly et al. (2006), none of these reviews adopt a systematic approach for identifying and collecting papers. Second, all these reviews tend to focus on particular
areas in OM, and contain only very limited applications to broader contexts in SCM (which is also due to the limited search scope). Third, the primary focus in most reviews is on particular methodologies, such as behavioral experiments (e.g., Bendoly et al., 2006; Knemeyer & Naylor, 2011), system dynamics (e.g., Größler et al., 2008; Bendoly et al., 2010) and/or analytical models (e.g., Boudreau et al., 2003; Loch & Wu, 2007). Studies using survey-based approaches, case studies and secondary data analyses were rarely included in the review and classification. Fourth, none of these reviews scrutinize the interrelationship between different studies to understand the evolution of BOSCM research.

The recent handbooks published by Bendoly et al. (2015) and Donohue et al. (2018) provide in-depth discussions on the main components of BOSCM research (e.g., theory, method, and some applications). Our systematic review leverages a more general view of the BOSCM literature that incorporates a broader range of efforts made in various knowledge areas of OM/SCM with respect to theories and methods adopted. We present a comprehensive review and bibliometric network analysis of BOSCM research published in top-tier OM journals. The review identifies the key knowledge areas that have informed BOSCM research from January 1, 1981 to the end of June 2018. We use a systematic approach and criteria/attributes to classify this literature, examine the interrelationship between various studies, and identify the informing areas that have helped shape the evolution of the field to date.

In what follows, we start our systematic review of the BOSCM literature by identifying relevant databases and keywords. We proceed to present a bibliometric analysis and the main clusters of articles informing BOSCM literature using a co-citation network analysis. We further provide detailed discussion of the pool of articles and the identified operations contexts informed by these clusters. Finally, we discuss the results obtained from a survey of some of the most prolific authors in this domain on the present status and outlook of BOSCM, which then enables us to draw our conclusions and provide some critical directions for future research in this area.
<table>
<thead>
<tr>
<th>Authors (year)</th>
<th>Focus and type of classification</th>
<th>OM areas covered</th>
<th>Reviewed journals</th>
</tr>
</thead>
</table>
| Bendoly et al. (2006) | Behavioral assumptions in OM research  
• Intensions  
• Actions  
• Reactions | • Product development;  
• Inventory management  
• Quality management  
• Production and workflow management  
• Procurement and strategic sourcing  
• SCM | JOM, MSOM, POM, MSJ, DSJ, and Journal of Applied Psychology |
| Loch & Wu (2007) | Individual decision making biases  
Social Preferences | General | Mostly economics journals  
Some papers from JOM, MSJ, OR, MSOM |
| Gino & Pisano (2008) | Incorporating behavioral and cognitive factors into OM models  
Focus on Heuristics and Biases | • Product development  
• R&D and project management  
• Supply chain  
• Forecasting  
• Inventory Management  
• IT management  
• Service operations | Mostly economics, organizational behavior and human resource management journals  
Some papers from JOM, MSJ, MSOM papers |
| Größler et al. (2008) | System dynamics  
• Feedback  
• Accumulation  
• Delays | • SCM  
• Improvement programs in operations  
• Project management  
• New product development, innovation, and diffusion  
• Effects of production technologies  
• Dynamics of maintenance and supply chains | Some papers from POM, JOM, MSJ, EJOR, IJPE and IJPR |
| Boudreau et al. (2003) | The interface between operations and human resources management | • Inventory  
• Server pooling  
• Production and workforce planning  
• Team build  
• Customer contact and quality  
• Bucket brigades  
• Low-inventory operation | MSJ, MSOM, OR, IIE Transactions, JOM, IJPR, IJPE |
| Bendoly et al. (2010) | Cognitive psychology  
Social psychology  
Group dynamics  
System dynamics | General | Mostly psychology, sociology and economics journals  
A few papers from OM journals |

2. Review methodology

In this section, we conduct a systematic review and network analysis of the BOSCM literature. Our goal is to identify the primary operational and behavioral domains represented as well as the methods and theories adopted. Systematic literature reviews aim to reduce the selection bias and errors in capturing papers published in a certain area by adopting an iterative process of defining and filtering keywords and validating search results (Saunders et al., 2009). The systematic review method adopted in this paper consists of the following phases (Hart, 1998; Bryman, 2012): (1) source identification, (2) source selection, (3) source evaluation, and (4) data analysis. The same approach has been used extensively in the OM literature (e.g., Giunipero et al., 2008; Spina et al., 2013; Maestrini et al., 2017). In the following sub-sections, we elaborate on the activities under phases 1-3, including basic bibliometric statistics related to phase 3. Phase 4, data analysis, is discussed in sections 3 and 4 in the form of co-citation network analysis and literature classification. These latter efforts are designed to identify and interpret the informing knowledge areas that have enabled BOSCM literature to shape and evolve over time.

2.1 Source identification and selection

We narrow down the scope of our review to top-tier OM/SCM journals, as recommended by www.scmlist.com. These include the eight journals of Management Science Journal (MSJ), Journal of Operations Management (JOM), Manufacturing & Service Operations Management (MSOM), Production and Operations Management (POM), Operations Research (OR), Journal of Supply Chain Management (JSCM), Decision Sciences Journal (DSJ) and Journal of Business Logistics (JBL). From this list, the five journals of MS, JOM, POM, MSOM and OR are on both Financial Times top 50 journals (FT 50) and The UTD Top 100 Business School Research Rankings™ (UTD) journal lists. We add to this list the more specialized journals of JBL, DSJ and JSCM, published respectively by professional associations of Council for Supply Chain Management Professionals (CSCMP) and Decision Sciences Institute (DSI) and Institute for Supply Management (ISM).

Designing an effective keyword structure that can capture most of the relevant papers is a major task for a systematic literature review. We define such a keyword structure through a rigorous process of trial and error. This structure includes two sets of keywords: a single-level set comprising the primary keyword pairs, and a two-level set comprising separate ‘operations’ and ‘behavioral’ keywords (see Table 2 for the details). Publications (articles and articles in press) from January 1, 1981 through to the end of June 2018 were considered in the review. Several search
attempts and comparisons of the records obtained from Scopus and ISI Web of Knowledge revealed that Scopus yields more accurate and relevant search outcomes. Similar examples in the OM/SCM literature show the preference of Scopus over ISI Web of Knowledge in systematic reviews (see for example Fahimnia et al. (2015a)).

The initial search attempts revealed 130 articles for the single-level and 327 articles for the two-level keyword sets with 81 articles common between the two sets. This gave us a total aggregated result of 376 records. To examine the inclusiveness of this pool of articles, we cross-checked the records against the reference lists of several special issue notes and review articles published in the area of BOSCM (i.e., Bendoly et al., 2006; Loch & Wu, 2007; Gans & Croson, 2008; Gino & Pisano, 2008; Bendoly et al., 2010; Donohue et al., 2010; Croson et al., 2013; Hamalainen et al., 2013; Katsikopoulos & Gigerenzer, 2013; Zhao et al., 2013). These comparisons resulted in some minor adjustments in the two-level keyword set. The final keyword sets in Table 2 were reviewed and endorsed by some of the leading scholars in the field whom we acknowledge at the end of this paper.

This refined keyword structure discovered 439 unique papers. The next stage of our research was to assess the inclusiveness of individual papers in this pool. We considered a paper to be in the area of BOSCM and hence eligible to be kept in the pool if

(1) it is within an OM/SCM context,
(2) it is behavioral in nature: a study that allows a deviation from any of the following (Croson et al. 2013): (A) decisions are motivated by self-interest, usually expressed in monetary terms; (B) decision makers act in a conscious/deliberate or non-emotional manner; and (C) models and decision makers behave optimally using a specified objective function, and
(3) it analyses the behavior of individuals or small groups of individuals at a micro-level (i.e. considering human cognition or psychology/sociology in the theoretical arguments).

Using the above eligibility criteria, 298 papers out of 448 were considered as directly or indirectly relevant to BOSCM research. We then used our keyword structure to directly search for papers in the database of the eight journals (not using Scopus as a database). Through this process, we identified an additional 55 relevant papers that were not captured by Scopus. These papers were added to the list, resulting in a pool of 353 papers. During the process of revising this paper for publication, we updated this list to include the published articles until the end of June 2018. The final number of papers included in the pool (including the ‘in press’ papers) was increased to 385, which will be used for further analysis and investigation in this paper.
It is worth noting that the list of our OM keywords in the ‘two-level’ search structure is not exhaustive. Adding additional keywords either did not make a difference in the search results or caused exponential increase in the number of irrelevant articles in the search results. Therefore, we adopted a hybrid method of using multiple keyword sets for online search, filtering and screening the search results, and manually adding the missing papers from the target journals. This was done through over 50 rounds of iterations. We believe that the final set of 385 papers well represents the BOSCM publications in the target journals.

Table 2 The keywords that were used in our Scopus search attempts

<table>
<thead>
<tr>
<th>Single-level search:</th>
<th>behavioral economics, behavioural economics, behavioral operations, behavioural operations, behavioral supply, behavioural supply</th>
</tr>
</thead>
<tbody>
<tr>
<td>Two-level search:</td>
<td>auction, beer game, bidding, bullwhip effect, capacity, channel coordination, demand management, demand planning, distribution channel, forecast, information sharing, inventory management, logistics, newsvendor, operations management, procurement, project management, resource planning, revenue management, supplier evaluation, supplier selection, supply chain, supply management, value chain</td>
</tr>
<tr>
<td>Level 1 (OM/SCM keywords)</td>
<td>AND anchoring, behavioral, behavioural, judgment, bounded rationality, boundedly rational, cognitive, cognition, experimental economics, fairness, feedback/control, framing, group dynamics, heuristic/bias, individual preference, inequality aversion, judging, loss-averse, loss averse, loss-aversion, loss aversion, prospect theory, psychology*, pull-to-center, pull to center, quantal response, random errors, reciprocity, reference dependence, risk-attitude, risk attitude, risk-averse, risk averse, risk-aversion, risk aversion, risk-neutral, risk neutral, risk preference, risk seeking, social preference, system dynamics, trust*</td>
</tr>
<tr>
<td>Level 2 (behavioral keywords)</td>
<td></td>
</tr>
</tbody>
</table>

Note: The ‘*’ shows that the term as well as variations of the keyword have been used in the search attempts

2.2 Source evaluation

A source evaluation consists of inductive or deductive classifications of the papers using a set of predefined criteria (Spina et al., 2013). To address this, in the following sections we discuss the bibliometric features of the extracted papers (section 2.3) and identify the operational contexts and functional tasks that allow us to classify the papers based on the OM/SCM contexts (section 4). We then further extract the main underlying behavioral theories applied in each context along with non-behavioral theories and the most frequent choice of methods in each context. Note that not
all of these 385 articles have been cited in this paper, but the complete source file and the evaluation results for the pool of 385 papers is available online on a Google Sheets platform¹.

2.3 Initial statistics

The analysis of the frequency of publications shows that BOSCM research began to gain momentum in 2005-2006. Thanks to seminal works such as Sterman (1988) and Schweitzer & Cachon (2000), the behavioral operations conference that started in 2006, and the follow up review papers of Bendoly et al. (2006), Gino & Pisano (2008) and Bendoly et al. (2010), some of the key research opportunities in the field were identified. The journals of MSJ (96 articles), POM (95 articles), and JOM (74 articles) have published the highest quantity of BOSCM articles. The earliest research in the collected pool of papers is the work of Adam (1981), who develops a behavioral program to track attitudinal changes in employees of a carrier trucking terminal. The extracted pool of papers contains only 15 articles published before 2000. Figure 1 shows the frequency of publications since 1981.

Figure 1. Publication trend in the pool of 385 articles (through to the end of June 2018)

The authors identified based on the quantity of published articles in the selected journals are Bendoly E. (21), Katok E. (20), Siemsen E. (16), Donohue K. (8), Croson R. (8), Zhao X. (7),

¹ Viewers can use the following address to access the Google Sheet document: https://docs.google.com/spreadsheets/d/12xeyRtsFAdz5RZJuxFepGpbe-FWJ3bVuivxNuVynMk/edit?usp=sharing
Kremer M. (7), Boyer K.K. (6), Davis A.M. (6), Eckerd S. (6), Loch C. (6), Moritz B. (6), Schultz K.L. (6). Some of these authors are the same as those we identify in this paper as prolific authors in BOSCM research and whom we also ask to comment on framing the boundaries of this review and proving directions for future research in their areas of expertise. We acknowledge their contributions at the end of this paper.

Some of the most frequent index keywords used in the pool of articles are behavioral operations, inventory control, experiments, game theory, newsvendor problem, management science, and decision theory. Figure 2 shows the word cloud of the most frequent index keywords with the frequency of two and above.

[Figure 2. Word cloud of the most frequent keywords in the pool of 385 articles]
3. Co-citation network analysis

Citation analysis argues that the most influential articles in a field of study are those with the highest number of citations (Garfield, 1979). Co-citation analysis refers to the frequency of two documents cited together in a selected pool of literature (Small, 1973). The assumption is that as the frequency of co-citation for two documents increases, the more likely it is for them to have similarities in the contents (Batistič et al., 2017). In the context of a systematic literature review, two articles are co-cited if they are cited in the same citing document.

Co-citation is dynamic as frequencies of co-citations between two articles can increase over time. It is known as a reliable method that reveals relationships between authors, sub-contexts in a field of study, journal, keywords, and research methods (Small, 1973). The greater the connection between two documents (i.e., the frequency of co-citations of the two documents), the more likely they are to form a cluster (Clauset et al., 2004; Leydesdorff, 2011). Each cluster can be seen as a group of articles that are strongly connected and have weaker connections with other clusters. Thus, each cluster can represent a research area which has informed the BOSCM field. From definitions of co-citation and cluster analysis, we find that the articles in each cluster may not be necessarily a BOSCM article (see Table 3), nor they need to necessarily cover the most recent publications in the BOSCM or non-BOSCM field. This is due to the reverse relationship between the date of publication and the citations an article receives from other scientific literature in order to be included in one cluster.

3.1. Methods applied to co-citation analysis

Sci2 Tool (Sci2, 2009) and Gephi 0.9.12 software packages are adopted in this paper to conduct a co-citation network analysis and visualization. Sci2 Tool is a versatile network analysis tool that accepts network data from a variety of sources (e.g., ISI Web of Knowledge, Scopus) and in a wide range of data formats (e.g., Bibtex, ISI flat, Scopus CSV). The database of OSCM articles from the selected journals was exported to Sci2 Tool in a CSV Scopus format for co-citation and co-authorship network analysis. The CSV file included data on authors, year of publication, title, journal, keywords, global citation, and references.

Similar to citation analysis, the nodes in co-citation analysis represent the articles cited by each article within the pool of 385 BOSCM articles. The edges between two nodes in co-citation analysis

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2 https://gephi.org/
show the appearance of the co-cited articles in the same citing article. Thus, while citation and co-
citation networks share the same nodes, the nature and role of edges differs in co-citation analysis
where the quantity of edges is substantially greater in strongly connected networks. Following the
principles of co-citation analysis, the total number of nodes in the pool of 385 BOSCM articles
were 17,649 (i.e., an average of 53 cited references per article) and the total number of edges were
707,170 (i.e., on average, each cited article has been co-cited with 40 different articles – no
overlaps). The network analysis outcomes using Sci² Tool show that the resulting co-citation graph
is well connected, which suggests the presence of meaningful clusters.

The in-degree of a node (i.e., the number of edges pointing into a node) shows the frequency of
the article cited concurrently with any other article within the pool by all citing articles. To develop
meaningful clusters that each contain the most related articles, the in-degree needs to be filtered
to a certain number so that the total number of nodes, edges, and clusters produce a meaningful
and manageable set of clusters. Gephi uses the Louvain algorithm, an iterative optimization model,
to determine the total number of clusters and to maximize the modularity index. The modularity
index which varies between -1 and +1 intends to compare link densities within and in between
clusters (see Fahimnia et al., 2015a; Fahimnia et al., 2015b). Applying this clustering model to the
co-citation network of BOSCM papers, four major clusters are created with the modularity of
0.355, which indicates a strong connection between nodes within clusters and also a strong and
yet distinguishable connection between nodes from different clusters.

The resulting clusters from Gephi were thoroughly analyzed by the authors in several review
rounds in order to identify the research focus of each cluster (i.e. cluster labeling) which implicitly
determine the key research streams constructing the BOSCM literature. Table 3 summarizes the
clustering results. In addition to labeling the clusters (i.e., BOSCM research streams – column 1 of
Table 3) and following the earlier discussions on the nature of the articles that can be expected to
emerge from co-citation and clustering analysis, we used labelling to discern between the articles
emerging in each cluster. Column 2 represents the identified OSCM articles in each cluster that in
some cases include BOSCM articles as well. Furthremore, we identify the informing areas of each
cluster (columns 3 and 4 in Table 3) including the foundational theories that informed the research
stream (column 3) and the key methodologies that informed research in each stream (column 4).
The identification and labelling of clusters and the informing areas involved two of the authors
reviewing the articles in each cluster independently and proposing their categorization with respect
to the proposed format for Table 3. These two categorizations were subsequently merged and
reviewed by all authors for validity and consistency. For each cluster, the last column of Table 3 provides the most related review papers.

PageRank analysis (originally proposed by Brin & Page, 1998 to understand the connectivity of webpages) is applied to each cluster as a measure to decide about prestige and popularity of each paper. PageRank evaluates the extent of a paper being co-cited with other papers as well as being co-cited with highly-cited papers, hence incorporating popularity and prestige of papers respectively. Using PageRank analysis is a common practice in co-citation analysis and especially among OSCM researchers (interested readers can find the mathematical details of PageRank analysis in Fahimnia et al. (2015a), Fahimnia et al. (2015b), and Xu et al. (2018)). PageRank is a probability distribution that ranges between 0 and 1 with higher PageRank value of a paper indicating greater prestige and popularity of that paper. Considering this and the fact that the number of articles in each cluster naturally varies, we applied a minimum PageRank score to ensure including at least 10 articles from each cluster and at least one article in each informing area. This has therefore resulted into some clusters having more than 10 articles to satisfy the aforementioned requirements.

3.2. Observations in research clustering

As can be seen in Table 3, there are a number of overlaps between different clusters where the same article may be included in two or more clusters (e.g., Schweitzer & Cachon (2000) and Bendoly et al. (2010) have been included in both clusters 1 and 2). This type of overlap is a common occurrence in network analysis (Palla et al., 2005; Ball et al., 2011) and indicates that the aforementioned articles have been commonly cited in multiple research areas. Articles in each cell of Table 3 are presented in alphabetic order.
<table>
<thead>
<tr>
<th>O SCM papers</th>
<th>Informing areas</th>
<th>Informing methodologies</th>
<th>Informing theories</th>
<th>Related review papers</th>
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<tbody>
<tr>
<td><strong>Cluster 1</strong></td>
<td>Risk management</td>
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<tr>
<td>March &amp; Shapira (1987)</td>
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<td>Narasimhan &amp; Talluri (2009)</td>
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<td>Schweitzer &amp; Cachon (2000)</td>
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<td>Tomlin (2006)</td>
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<td>Zsidisin (2003)</td>
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<td><strong>Cluster 2</strong></td>
<td>Inventory management</td>
<td>Behavioral experiments</td>
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<td>Bendoly et al. (2010)</td>
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<td>Croson &amp; Donohue (2006)</td>
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<td>Su (2008)</td>
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<tr>
<td>Schweitzer &amp; Cachon (2000)</td>
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<tr>
<td><strong>Cluster 3</strong></td>
<td>Buyer-supplier relationship</td>
<td>Multivariate statistical analysis</td>
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<td>Terpend et al. (2008)</td>
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<td>Carr &amp; Pearson (1999)</td>
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<td>Daniel Corsten &amp; Kumar (2005)</td>
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<td>Doney &amp; Cannon (1997)</td>
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<td>Dwyer et al. (1987)</td>
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<td>Ganesan (1994)</td>
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<td>Gudnitz &amp; al. (1995)</td>
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<td>Kahwani &amp; Narayandas (1995)</td>
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<td>Kaufmann &amp; Carter (2006)</td>
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<td>Kwon &amp; Suh (2004)</td>
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<td>Lawson et al. (2008)</td>
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<td>Maloni &amp; Benton (2000)</td>
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<td>Morgan &amp; Hunt (1994)</td>
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<tr>
<td><strong>Cluster 4</strong></td>
<td>SCM</td>
<td>Theory building and multivariate statistical analysis</td>
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<td>Cooper et al. (1997)</td>
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<td>Monezka et al. (1998)</td>
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Table 3 provides several interesting insights. One whole stream in our co-citation network analysis (stream 1) is assigned to operations risk management studies in a supply chain context (e.g., Kraljic, 1983; Kleindorfer & Saad, 2005) with some related behavioral studies (e.g., Schweitzer & Cachon, 2000; Ellis et al., 2010). The main methodological papers in this cluster focus on behavioral experiments (e.g., Bachrach & Bendoly, 2011; Siemsen, 2011) and multivariate statistical analyses methods such as structural equation modeling (e.g., Anderson & Gerbing, 1988). Multi-variate statistical methods are commonly used by authors in Clusters 1-3-4 which clearly indicates that a significant number of studies in these clusters are founded on survey methods and empirical research. The main behavioral studies informing Cluster 1 papers are around the psychology of decision making in terms of cognitive limitations in decision making (Tversky & Kahneman, 1974), perception of risk and risky decision making (Sitkin & Weingart, 1995) and the role of intuition in managerial decision making (Dane & Pratt, 2007). Half of the studies in this cluster refer to BOM review papers (Bendoly et al., 2006; Bendoly et al., 2010) and the other half cite behavioral supply management reviews (Carter et al., 2007; Tokar, 2010).

Cluster 2 focuses on behavioral inventory management either by investigating the newsvendor problem (Agrawal & Seshadri, 2000; Schweitzer & Cachon, 2000; Su, 2008) or by studying the behavioral causes of the bullwhip effect (Croson & Donohue, 2006). Most studies in this area are conducted using behavioral experiments. The main methodology paper informing these studies is the work of Croson & Donohue (2002) in which the authors discuss how experimental economics methods could be tailored for use in OM and SCM problems. The psychological studies informing this cluster deal with cognitive limitations and risk attitudes (Tversky & Kahneman, 1974; Kahneman & Tversky, 1979; Tversky & Kahneman, 1985), bounded rationality (Conlisk, 1996) and bipolarity in operational decision making (Bendoly & Hur, 2007). BOM review papers of Bendoly et al. (2006) and Bendoly et al. (2010) have informed the studies of this cluster.

Cluster 3 contains articles that investigate buyer-supplier relationship especially through the lens of trust (Kwon & Suh, 2004), power (Brown et al., 1995) or both (Ireland & Webb, 2007). Except for a handful of studies that are published by JOM, most articles have a marketing focus, mainly published in Journal of Marketing. Most theoretical and behavioral/psychological papers informing this cluster adopt a ‘social’ lens (e.g., Blau, 1964; Vroom, 1964). Resource-based view (Peteraf, 1993) and social exchange theory (Griffith et al., 2006) have been the fundamental theoretical frameworks. The main review article in this cluster is the work of Terpend et al. (2008) which classifies published research on buyer-supplier relationship.
Cluster 4, in essence, includes studies focusing on extended SCM topics such as supply chain planning (Oliva & Watson, 2011), supply chain integration and strategic alliances (Monczka et al., 1998; Frohlich & Westbrook, 2001; Fawcett & Magnan, 2002) and green SCM (Zhu & Sarkis, 2004). The main psychological frameworks informing these articles revolve around trust and social psychology (Dawes, 1980; Rousseau et al., 1998) and debiasing methods (Kaufmann et al., 2009). Theory of sustainable SCM (Pagell & Wu, 2009) is the primary theoretical framework in this cluster. Two holistic reviews of SCM Cooper et al. (1997); Narayanan et al. (2015) are associated predominantly with articles in this cluster.

3.3. Limitations of co-citation analysis

Despite its applicability in identifying influential journals, papers and authors, citation analysis is subject to a number of caveats that diminishes its popularity in systematic literature reviews (see Pilkington & Meredith, 2009 for more details) and could not be used in this paper. As for the co-citation analysis in this section, it is important to note that although the clusters from the co-citation analysis shed some light on the foundations on which modern BOSCM has built, they have a number of limitations. First, there is a time limitation to the articles appearing in each cluster. That is partly due to the fact that the earlier an article is published, the more time it has had to develop citation and co-citation with other articles; hence the higher chance of appearing as a prestigious and popular article in a given cluster. This is reflected in Table 3 in which most articles date back to 1990s and 2000s. Second, only multi-disciplinary articles appear in a co-citation analysis, in this case articles representing various knowledge areas such as OSCM, BOSCM as well as Psychology and Marketing. Lastly, Table 3 only shows the most notable clusters and articles out of 17,649 nodes (the total number of cited articles) in the co-citation graph.

As a result, while this clustering provides a generic view of the knowledge areas that have informed BOSCM research, it does not clearly identify emerging research areas. To understand the latest developments in the BOSCM field, a more meticulous investigation of the BOSCM literature is required. This is the grounds for our literature classification of the BOSCM articles in section 4. Such a classification of published BOSCM studies is intended to provide a more in-depth view of the current state of the field as well as the relevance of these studies relevance to each cluster mentioned in Table 3.
4. Literature classification based on operations contexts

We adopt a procedure for qualitative content analysis (Strauss, 1987; Corbin & Strauss, 2015). Each co-author on this manuscript independently assigned the identified articles to the most relevant OSCM category. The OSCM categories are based on the existing classifications proposed in OM and SCM handbooks (e.g., Slack et al. (2016)). Next, the co-authors compared their classifications and arrived at a consensus where discrepancies existed. A final document was then developed and double-checked by all co-authors for consistency and reliability.

As we observed, there are arguably articles in the BOSCM literature that could be located within multiple OSCM categories. However, to avoid repetitions, we discuss each study only once under the most related OSCM category. Based on the frequency of publications per category, we observe that SCM (71 articles), inventory management (56 articles), and procurement and auctions (52 articles) have been the most popular BOSCM research areas (see Appendix A). We also point out that for some of these areas – such as forecasting and product development – a substantial literature also exists in other journals which were not included in our initial search space (e.g., papers published in International Journal of Forecasting, Organization Science, and Research Technology Management). At the end of our discussions for each category we identify the main clusters from section 3 informing the studies in the category. This is done by tracing back the OSCM studies, informing methodologies, theories and review papers (section 3) cited by the articles in each category. Table A1 in Appendix A shows the frequency of research methods per each operations context. The order of presenting the categories below is based on the decreasing frequency of publications per category.

4.1 SCM

It was predictable that most articles in our database would belong to this operations context given the growing significance of SCM research in general. Behavioral studies in SCM comprise sub-categories including supply chain contracting, inventory management and the bullwhip effect, buyer-supplier relationships, and information sharing. Here, we briefly touch upon the scope of studies under each of these sub-categories, while leaving behavioral inventory management studies for discussion in a separate category in section 4.2.

Most behavioral supply chain contracting studies have focused on risk-attitudes of decision makers and specifically risk aversion and loss aversion traits and their impact on supply chain contracts and their coordinating parameters (Xin et al., 2014; Davis, 2015). Prospect theory is the primary
perspective used in these studies (Kahneman & Tversky, 1979). Another stream of research under supply chain contracting is concerned with fairness in supply chain contracts (Katok & Pavlov, 2013; Ho et al., 2014; Yi et al., 2018) which uses inequality aversion models for investigating the related topics (Fehr & Schmidt, 1999; Bolton & Ockenfels, 2000). The most widely adopted research methods in these articles are analytical modeling and behavioral experiments.

Behavioral studies on buyer-supplier relationships cover a variety of topics. Some topics are emerging and provide unique opportunities for research. These topics are discussed in section 4.13. One of the more established topics is the power balance and trust level between buyers and suppliers and its operational implications (Ireland & Webb, 2007; Terpend & Ashenbaum, 2012; Pulles et al., 2014; Brito & Miguel, 2017; Aral et al., 2018; Kaufmann et al., 2018). Other related topics are supply chain integration (Enz & Lambert, 2015; Thornton et al., 2016) and supplier development and knowledge transfer (Kim et al., 2015; Preston et al., 2017). Some of the most popular operational and behavioral theories used for behavioral buyer-supplier research are social network theory (Newman, 2003), social exchange theory (Blau, 1964), social capital theory (Nahapiet & Ghoshal, 1998), and transaction cost economics (Williamson, 1979). Survey and behavioral experiments have been the most popular research methods in these studies.

Behavioral implications of information sharing among supply chain tiers is another area of research focus under behavioral SCM. Some studies in this category discuss the role of trust and trustworthiness in information quality and demand forecasts shared between various supply chain participants (Bolton et al., 2004; Cai et al., 2010; Ebrahim-Khanjari et al., 2012; Spiliotopoulou et al., 2016). Other studies investigate the behavioral consequences of information sharing on overall supply chain performance and coordination (Cantor & Macdonald, 2009; Inderfurth et al., 2013) and supply chain partnerships and relationships with external stakeholders (Ren et al., 2010; McCarter & Fudge Kamal, 2013). Several operational and behavioral theories have been used, among which game theory could be the most widely adopted. Analytical modeling and behavioral experiments have been the most frequently used research methods.

A few studies have explored behavioral logistics management topics including the role of trust, loyalty and justice in logistics outsourcing (Wallenburg et al., 2011; Hofer et al., 2012), fast decision making in humanitarian logistics operations (Gralla et al., 2016) and behavioral studies related to congestible networks and traffic routes (Mak et al., 2015). Social exchange theory has formed the main theoretical framework in these studies. Surveys, behavioral experiments and observations have been widely used for data collection.
Overall, because SCM is so multifaceted and integrally connected across strategic functional domains, the contributions of associated behavioral research echo aspects of each. Distinctions in the incentives of collaborating parties, their alternative risk views, their network connectedness and perceived (and real) obligations to other network partners, all complicate information processing. The existence of information external to the organizational limits of decision makers further creates imperfect information settings which encourage the use of heuristics and the role of personal biases and system perspectives. It is clear from these studies that increased data and knowledge exchange can reduce the risk of informational gaps. However, it is also clear that the choice of sharing information and the interpretation of that information remains subject to seemingly non-rational mechanisms that may be driven largely by social structures and dynamics.

There are a few papers in this area that contribute through discussions of the design of behavioral experiments and related tools, as well as sampling methods for behavioral studies in logistics and SCM (see for example, Bachrach & Bendoly, 2011; Knemeyer & Naylor, 2011; Rungtusanatham et al., 2011; Siemsen, 2011; Thomas, 2011). These discussions are arguably applicable across domains of interest, and represent useful sources for scholars aiming to learn about behavioral tools and experiment design in general. All four clusters from section 3 show proximity to this category as there are relevant studies in this category to behavioral studies on risk, supply chain risk management, buyer-supplier relationship, inventory management and supply chain management. In addition, analytical modelling, behavioral experiments and surveys have all been popular research methods in this category (see Table A1).

4.2 Inventory management

Most studies in this category investigate ordering behavior in a newsvendor setting. The number of published articles in this area is constantly increasing to the point that almost half of all articles in this area have been published between 2013 and 2016. This observation is consistent with the overall importance of the newsvendor problem in the field of operations management as one third of all publications in Production and Operations Management Journal use the word newsvendor in their text (Zhang & Siemsen). One of the seminal papers in this area is the work of Schweitzer & Cachon (2000), who studied a number of behavioral regularities in ordering such as risk attitudes (i.e., risk neutrality, risk aversion and risk seeking, loss aversion, prospect theory), anchoring and insufficient order adjustments in high-profit and low-profit newsvendor settings under different demand scenarios. Other newsvendor studies investigated behavioral models such as bounded rationality (Su, 2008), risk aversion and expected utility maximization (Agrawal & Seshadri, 2000; Chen et al.,
2007; Chen et al., 2009; Choi et al., 2011; Kremer & Van Wassenhove, 2014), reference dependence and pull-to-center bias (Ho et al., 2010), cognitive reflection (Moritz et al., 2013), overconfidence (Ren & Croson, 2013; Li et al., 2017), mental accounting (Chen et al., 2013b), prospect theory (Nagarajan & Shechter, 2014; Long & Nasiry, 2015; Schultz et al., 2018), and judgment bias (Tokar et al., 2014) to explain ordering behavior of decision makers in various circumstances.

There are also studies on behavioral factors that could improve decision making and mitigate risks of biased decisions in a newsvendor setting (e.g., Tomlin & Yimin, 2005; Bolton & Katok, 2008; Ockenfels & Selten, 2015; Ovchinnikov et al., 2015; Feng & Zhang, 2017). The ordering behavior could be affected by the background of the decision makers. This has been investigated in different contexts including the behavior of managers vs. students (Bolton et al., 2012), females vs. males (de Véricourt et al., 2013), and Chinese vs. Americans (Cui et al., 2013). Another class of studies explores the behavioral causes of the bullwhip effect in the supply chain (e.g., Croson & Donohue, 2006; Croson et al., 2014; Narayanan & Moritz, 2015; Tokar et al., 2015) and solutions to mitigate the identified behavioral risks (Wu & Katok, 2006; Tokar et al., 2012).

Behavioral theories explaining risk attitudes such as expected utility theory and prospect theory have been extensively adopted. Behavioral experiments and analytical modeling have been the most frequently used research methods. The primary contributions of studies in this focus area involve the development of specific models to capture behavior in the specific settings under investigation. The benefit of targeted behavioral investigations in contexts with limited complexity has been the development of a foundation of further modeling considerations in more complex real-world settings. These fundamental investigations have therefore provided a critical grounding for much of contemporary efforts to study real-world phenomena across OSCM contexts. Clusters 1 and 2 (section 3) show the most proximity to this category as there are relevant studies in this category to decision biases (Cluster 1) and attitudes toward risk and prospect theory (Cluster 2) as well as the preference to use analytical modelling and behavioral experiments as the most preferred research method (see Table A1).

### 4.3 Procurement and auctions

A considerable number of papers have been published on behavioral decision making in procurement and auctions, a sub-stream of SCM research. Published papers in this category belong to one of the two areas of ‘auctions’ and ‘buyer-supplier relations’. The earlier behavioral studies on auctions mainly focused on the interactions between suppliers and buyers (or consumers or bidders) in electronic reverse auctions (Carter & Kaufmann, 2007; Carter & Stevens, 2007;
Yeniyurt et al., 2011). The focus later shifted to other types of auctions such as ascending auctions (Kwasnica & Katok, 2007), blind auctions (Engelbrecht-Wiggans & Katok, 2008), combinatorial auctions (Adomavicius et al., 2012), and multi-object auctions (Bichler et al., 2015). The most dominant theoretical framework has been auction theory (e.g., Bajari & Summers, 2002; Zeithammer, 2006; Marshall & Marx, 2012). Behavioral experiments have been the most commonly used research method.

Behavioral studies on buyer-supplier relations could be classified under either ‘SCM’ or ‘procurement and auctions’ contexts. We chose to include them under ‘procurement and auctions’ due to the more specialized nature of this category. Some studies in this area investigate the supplier selection problem through a behavioral lens, focusing on behavioral models such as trust (Huang et al., 2008), procedural rationality (Riedl et al., 2013), and attitudes toward risk and perception of control (Kull et al., 2014) affecting supplier selection decisions/processes. Another group of studies examine how the quality of buyer-supplier relationship affects operational, relationship or agility performance (e.g., Liu et al., 2012; Narayanan et al., 2015; Whipple et al., 2015). One stream of research in this area considers buyer-supplier relationship as a dependent variable upon behavioral factors such as culture (Ribbink & Grimm, 2014), buyer and supplier perception of collaborative relationship (Nyaga et al., 2010), buyer perception of supply risk (Ellis et al., 2010) and supplier’s reputation (Wagner et al., 2011).

Along with auction theory, viewed more broadly, social exchange theory has been predominantly used in these studies. Surveys have been the most common research method in most empirical studies. Similar to the SCM context in general, contributions in the focus area of procurement and auctions largely highlight the impact of perception and incentive differences across dyads. However, the implication extends to more complicated networks and multi-agent network settings. Long standing management concepts such as trust recast as elements of prior experience in these findings, establishing a ground for potential empirically supported Bayesian investigations of repeated auction policy and activity. Cluster 3 (section 3) show the most proximity to this category as there are relevant studies in this category to buyer-supplier relationship as well as the preference to use behavioral experiments as the most preferred research method (see Table A1).

4.4 Service operations

The number of behavioral studies in the context of service operations has been constantly growing during the past 15 years. The subjects of study in this domain are usually either customers (Ho & Zheng, 2004; Aksin et al., 2007; Huang et al., 2013; Yang et al., 2018) or employees (Oliva &
Sterman, 2001; Tan & Netessine, 2014). There are also studies that investigate buyer-supplier (service provider) relations and the impact on the quality of service operations (Handley & Benton Jr, 2012). Research has often focused on hospitals and healthcare providers (Chen et al., 2013a; McCoy & Lee, 2014; Tan & Netessine, 2014) as well as grocery supply chains (Boyer & Hult, 2005; Shockley et al., 2011; Wang & Zhou, 2018).

Queuing theory is often used to develop models for supervising customer queues (Kc & Terwiesch, 2009; Huang et al., 2013; Shunko et al., 2018). A variety of behavioral models and theories have been applied (e.g., bounded rationality and power) to study the behavior of customers (Handley & Benton Jr, 2012; Huang et al., 2013; Li et al., 2016; Kong et al., 2018) and workers/managers (Oliva & Sterman, 2001). Inequality aversion (e.g., Gu & Ye, 2014; McCoy & Lee, 2014) and equity theory (e.g., Boyer & Hult, 2005) were used to investigate customer behavior. Earlier studies mainly adopted archival data and survey methods. More recently, analytical modeling has become more prominent again.

Limitations to information availability, and to cognitive processing, are clearly as relevant to strategic foci on customer service as they are to the production operations and innovation domains. Findings in this domain illustrate the critical nature of the customer-server dyad, where non-rational behavior by both sides is both common and highly confounding in its interaction. Quality of service, for example, is not something that can be effectively analyzed without the consideration of information processing challenges faced on either side of a service dyad. Clusters 2 and 3 (section 3) show the most proximity to this category. There are relevant studies in this category to bounded rationality (Cluster 2) and power (Cluster 3), and buyer-supplier relationship (Cluster 3). With respect to methods, there is a preference to use surveys (Cluster 3) and analytical modelling (Cluster 2) (see Table A1).

4.5 Project management

Studies concerned with behavioral issues in project management have received more attention during the past few years, especially welcomed by the Production and Operations Management and Decision Sciences journals. While there is no single dominant topic in this context, topics such as whistleblowing (Park & Keil, 2009; Keil et al., 2010), task design, interdependence and difficulty (Katok & Siemsen, 2011; Chandrasekaran & Mishra, 2012; Schoenherr et al., 2017), and innovation (Lee et al., 2011; Hutchison-Krupat & Chao, 2014) have been investigated more than others.
Behavioral theories associated with social psychology and group dynamics such as groupthink (Janis, 1982) and goal-setting theory (Bandura & Cervone, 1983; Kanfer, 1990) have been broadly adopted in these studies. Surveys have been the most popular research methods in this context. Expectancy theory is also used to help describe group dynamics in such settings (Bunderson & Sutcliffe, 2002).

Findings from these studies emphasize the impact of various forms of complexity on information processing in project settings. This reinforces prior conclusions that increased challenge can in fact prove to be much more disruptive than motivational in many cases (Bendoly & Prietula, 2008). It is also clear from this body of research that the interactions between members of a team in project management settings can prove both beneficial as well as stifling dependent upon the level of interdependence, variety of perspectives and novelty of project work. Cluster 3 (section 3) shows the most proximity to this category as there are relevant studies in this category to social psychology as well as the preference to use surveys as the most preferred research method (see Table A1).

4.6 Revenue management

Studies in this group primarily investigate consumer and seller behavior under various pricing strategies (Ovchinnikov, 2011; Mak et al., 2014; Li & Jain, 2016; Özer & Zheng, 2016; Kremer et al., 2017; Qiu & Whinston, 2017). Another stream of research in this group studies capacity management issues and customer behavior in terms of capacity expectations (Liu & Ryzin, 2011), retention decisions (Ovchinnikov et al., 2014) and change of buying behavior using different incentives (Liu & Ryzin, 2008). Other studies focus on optimizing the pricing and revenue generating strategies in different areas and industries such as airlines (Vulcano et al., 2010), arts (Tereyagolgu et al., 2018) and hospitality (Bendoly, 2013). Another research stream in this operations context re-evaluates decision making errors and judgement biases in revenue management practices (Bearden et al., 2008; Bendoly, 2011; Kocabiyikoglu et al., 2015). In a recent study, Hu & Nasiry (2018) determine optimal pricing policy of a firm by showing market responsive to consumer behavior concerning gains or losses.

Game theory and prospect theory are broadly applied in these studies. Analytical modeling has been the common research method. The primary contributions of behavioral studies in the revenue management context lay in outlining some of the fundamental causes of missed revenue opportunities. Specifically, complexity and time pressure, much like in the context of new product development, play particularly significant roles in driving judgement errors and deviations from economically optimal behavior. This is the case even in the presence of fairly well codified best
practices in revenue management settings. The conclusion is that even in the presence of established rules for maximizing yield, individuals subject to greater pressures from time and complexity are increasingly susceptible to biases that can systematically reduce the effectiveness of decision-making. Cluster 2 (section 3) shows the most proximity to this category as there are relevant studies in this category to prospect theory as well as the preference to use analytical modelling as the most preferred research method (see Table A1).

4.7 Forecasting

One of the emerging areas within the context of BOSCM is studying the role of human judgment in forecasting. Studies have been completed on judgmental forecasts (Sanders & Ritzman, 1995; Kremer et al., 2011; Moritz et al., 2014; Seifert et al., 2015; Kremer et al., 2016; Petropoulos et al., 2018), judgmental adjustments to forecasts (Önkal et al., 2008), human behavior in the use of forecast support systems (Hoch & Schkade, 1996), overconfident forecasts (Grushka-Cockayne et al., 2017), and the role of trust and incentives in forecast sharing (Terwiesch et al., 2005; Özer et al., 2011; Özer et al., 2014; Scheele et al., 2018). In a recent study, Tong et al. (2018) investigated demand censorship bias in the newsvendor setting and techniques to reduce it.

The use of theory in this context is rather limited, but game theory has been the guiding theory for forecast sharing studies. Behavioral lab experiments have been the most popular research method for studies on judgmental forecasting and judgmental forecast adjustments. A main conclusion of this literature is to see judgmental forecasting as an often necessary evil – human forecasters introduce much intentional and unintentional bias into forecasts, but often represent the only feasible way for firms to incorporate information about promotions, competitors and the product portfolio into the forecast. Small judgmental forecast adjustments tend to decrease forecast performance (Li et al., 2018), whereas large adjustments increase performance. Limiting when and how people can adjust the forecasts made by an algorithm is thus an important aspect to understand in the design of forecasting processes. Cluster 1 (section 3) shows the most proximity to this category. There are relevant studies in this category to the psychology of decision making as well as the preference to use behavioral experiments (see Table A1).

4.8 Quality management

Most publications on behavioral quality management date back to 2000s, however our data shows that particularly since 2017 there has been growing interest in the topic in the selected eight OSCM journals. The publications in this context focus on topics such as the link between quality and
employee perceptions of safety (Das et al., 2008), goals and goal theory (Linderman et al., 2006), warranties (Balachandran & Radhakrishnan, 2005), and employee satisfaction and loyalty (Jun et al., 2006). In the most recent studies, Agrawal et al. (2015); Abbey et al. (2017) use both a survey and experiments to investigate consumers’ perception of quality for remanufactured products and factors affecting their willingness to pay for them. Davis & Hyndman (2018) focus on the role of relational and/or monetary incentives on supply quality and supply chain efficiency. Ren et al. (2018) consider bounded rationality of customers in perceiving quality of services and characterize the service provider’s decision of quality, pricing, control and information disclosure.

Theories used in these studies are diverse, but the use of surveys is the most common research method. In many respects the examination of quality efforts and implemented programs are emblematic of behavioral studies of enterprise technology implementations and associated organizational change (for more details, see Bendoly & Cotteleer, 2008; Schoenherr et al., 2017). In both cases, processes are almost always altered in ways that prove disruptive, or at least seemingly so, to some subset of the organization. As a result, the long-term performance of these efforts and the externalities associated with them are often distinct from short-term individual and organizational responses, and from normative expectations of returns from rational use.

Studies in this focus area have contributed to the general knowledge of quality management through connecting perspectives from organizational and consumer psychology. Incentives are at the heart of many of the perceptions relevant in this focus area, and therefore prove critical in determining the nature of information processing, relevant biases and ultimately the path of quality progress and its performance. Due to the diversity of theories and low frequency of publications in this category, we were not able to assign a cluster from Table 3 to this category.

4.9 Capacity Management

Despite the common aspects of behavioral studies in revenue management and capacity management, we discuss them in two different groups since we believe there are topics specific to each operations context that promises new research opportunities in the future. Amongst studies on capacity management, a nascent research stream is behavioral issues in allocating capacity. Examples of articles in this research stream include capacity management in the assignment of arriving jobs with fairness concerns (Geng et al., 2015), retailer’s perception bias while experiencing supply shortage (Chen & Zhao, 2015) and overestimation of monetary value of substituting products in the presence of demand and operational uncertainties (Bansal & Moritz, 2015). Other examples are focused more on supply-side dynamics, and include studies of supplier capacity
allocation to customers with past recollection of service capacity (Adelman & Mersereau, 2013), supplier behavior under capacity investment competition (Hu et al., 2017) and bounded rationality amongst supply chain members in allocating capacity (Chen et al., 2012). Behavioral experiments and analytical modeling have been the most common research methods in this category. In this domain, as with that of revenue management, contributions largely reinforce the negative role of time pressure and forms of capacity scarcity on decision-making. Notably, the role of external organizational agents as simultaneous decision-makers complicates many of these capacity management investigations, giving rise to novel opportunities but also further challenging the determination of optimal allocation decisions. Cluster 2 (section 3) shows the most proximity to this category as there are relevant studies in this category to bounded rationality as well as the preference to use analytical modelling as the most preferred research method (see Table A1).

4.10 New product development

There has been a growing interest in behavioral research in new product development over the past two years. Originally, articles in this domain were based on behavioral concepts such as the endowment effect (Thaler, 1980; Kahneman et al., 1990; Kahneman et al., 1991) and hyperbolic discounting (Loewenstein & Prelec, 1992), and investigate consumer behavior in product customization (Franke et al., 2010) and the choice between modular vs. integral products (Ülkü et al., 2012). Other studies (Burg & Oorschot, 2013; Sosa, 2014; Chen et al., 2015) were focused on collaborations between individuals or entities and behavioral concepts such as social embeddedness (Granovetter, 1985), fairness perceptions (Colquitt, 2001) and autonomy (Langfred, 2005) that are essential to consider when designing a new product or developing a new technology.

More recent studies have investigated the role of regret and risk taking and product innovations and product technology management (Jiang et al., 2017; Loch, 2017). Wuttke et al. (2018) investigate the main characteristics of innovation projects contributing to a supplier’s acceptance of innovation and new product development through a controlled lab experiment. Yan et al. (2018) pursue a similar line of research, i.e. supplier’s involvement in a buyer’s new product development. However, they focus on the impact of the uncertainties associated with new product development projects, buyer risk aversion and buying firm’s effort share on contractual decisions. Schiffels et al. (2018) conduct experiments to understand the impact of cognitive limitations on portfolio selection of new product development projects. Studies into the biases towards and impacts
associated with the reduction of certain aspects of new product cycle times (Bendoly and Chao 2016) have shed light on traps common to innovation processes.

Data in this domain primarily originates in behavioral experiments and surveys. Various theoretical frameworks have been adopted in these studies with no specific theory being dominant. Some of the related and broadly adopted theories include temporal construal theory (Trope & Liberman, 2000) to assess the desirability of products in time by the customers (Ülkü et al., 2012). In other cases, social network theory of structural holes (Burt, 1992) has been adopted to explain how social investment in dyadic relations could contribute to communication between two parties (e.g., colleagues) and for the recipient (e.g., developers responsible for product design) to accept the proposed rework (Sosa, 2014).

The findings from these studies reveal several critical phenomena in the new product development context. First, the manner in which task information is disclosed (e.g. reward vs. penalty framing) significantly impacts action taken by key players in innovation processes. Second, the timing of innovation is highly associated with threats and opportunities, and thus creates significant pressure on decision-making which can further limit rational processing. Risk aversion is a relevant force with regards to the impact of both issues in these high uncertainty contexts. Clusters 1 and 3 (section 3) show the most proximity to this category. There are relevant studies in this category to risk taking behavior (Cluster 1) and buyer-supplier relationships (Cluster 3). The two most popular research methods are survey and behavioral experiments (Table A1).

4.11 Production management

Behavioral studies in the production management domain are quite diverse, looking at production planning issues through the lenses of customers (Merle et al., 2010), production line workers (Schultz et al., 2010; de Leeuw & van den Berg, 2011; Vidal & Nossol, 2011; Hussain & List, 2012), and managers (Bendoly et al., 2008). Several other studies leverage behavioral methods and estimations to develop mathematical models of production planning (Troutt et al., 2006; Kazaz & Webster, 2011). The primary focus of these studies is on the behavioral implications of performance assessment practices related to productivity and performance of production line workers (e.g., de Leeuw & van den Berg, 2011; Vidal & Nossol, 2011; Hussain & List, 2012).

The behavioral foundations and theories adopted in these articles include the use of ‘understanding, focus on improvement, and motivation and goal setting theory’ (Locke & Latham, 2002) to understand how performance management can help achieve organizational goals (de
Leeuw & van den Berg, 2011); the use of prospect theory (Kahneman & Tversky, 1979) to understand how incentives framed as losses and gains affect productivity of individuals and teams (Hossain & List, 2012); the use of incentive theory (Lazear, 1989) and the application of performance feedback on workers’ performance (Vidal & Nossol, 2011). These studies often utilize archival data; however, surveys and field experiments have also been popular in this domain.

Contributions of these behavioral studies to the production management context are aligned with those in the new product development context, and hence highlight common threads of interest to firms thinking strategically with regards to both operational excellence and innovation. These include the critical role of informational presentation (framing) on worker and manager behavior. Findings emphasize the importance of transparency and feedback designs as part of overall incentive management. Effective designs along these lines have positive implications for productivity, and an account for variation in the throughput of these settings. Clusters 2 and 3 (section 3) show the most proximity to this category as there are relevant studies in this category to motivation and prospect theory and the preference to use first surveys and second behavioral experiments and analytical modelling as the most preferred research methods (see Table A1).

4.12 Process improvement

The subjects of behavioral studies on process improvement vary and encompass different stakeholders such as customers, employees, and managers. For instance, Lai et al. (2013) explore customer satisfaction with ERP implementation through perceived service quality and customer trust. Also at the organizational-process level, Bendoly and Corteleeer (2008) investigate the phenomena of resonant dissonance, and the associated lagged observation of enterprise system circumvention and process reversion through learning. At the group-process level, Kennedy et al. (2010) argue how team dynamics and performance can benefit from computer-aided or face-to-face meetings. At this level, the role of systems thinking within project groups (Bendoly 2014) has also shed light on innovation process dynamics, with associated links to limitations in cognitive processing.

Process investigations of behavioral action at the individual level have also received close investigation. DeHoratius & Raman (2007) explore how store manager behavior is affected by changes in incentives, and the subsequent impacts on inventory levels and sales performance. There are also studies focusing on behavioral antecedents of knowledge sharing among employees and how improved knowledge sharing could result into process improvement (Siemsen et al., 2008; Siemsen et al., 2009).
No single behavioral or operational theory stands out in this operations context. Amongst the adopted theories are cognitive appraisal theory (Folkman et al., 1986) and bounded rationality (Luce, 1959). Archival documents and behavioral experiments have been the primary data collection and research methods. Contributions to the broad-spanning relevance of the process management context, from these studies of behavioral operations, begin with a somewhat nuanced view of what processes are. Processes are too often viewed as linear, and hence managed by fundamentally constrained consideration. While this can make them tractable, it can also underestimate critical recursive aspects of real-world processes and changes in the dynamics of these processes over time. Technology provides assistance in the way organizations, groups and individuals systematically think about processes. Significant changes to technology and processes however also have lagged effects, capturing learning and adaptation. The potential for these lagged effects must be factored into any process improvement and management plan. Cluster 2 (section 3) shows the most proximity to this category as there are relevant studies in this category to bounded rationality as well as the preference to use behavioral experiments as the most preferred research method (see Table A1).

4.13 Emerging topics in BOSCM studies

The research contexts identified and discussed earlier are well-established. There are in addition emerging and promising BOSCM areas that have been formed though combining behavioral studies and popular/practical OSCM topics. We now discuss some of these emerging areas. One emerging and promising area is the behavior of supply chain members when disruptions occur (Gurnani et al., 2014; Wang et al., 2014). Some studies investigate how supply chain risks are perceived and how decision makers react to various types of risks (Ellis et al., 2011; Tazelaar & Snijders, 2013; Reimann et al., 2017). A focus on sustainable supply chain practices is another emerging topic in behavioral buyer-supplier relations that specifically studies behavioral anomalies of supply chain decision makers and employees in adopting sustainability-related strategies (Cantor et al., 2012; Kirchoff et al., 2016) and how a new logic and culture rooted in cognition can encourage supply chains to move down the sustainability path (Montabon et al., 2016). In a recent study, Soundararajan & Brammer (2018) investigate how intermediaries’ framing of social sustainability requirements affects sub-suppliers’ perception of fairness and their positive or negative reciprocation.

Innovative BOSCM methodologies may also initiate a stream of research. For instance, Kagan et al. (2018) use a unique data collection method to study the effect of product development
schedules on design strategies. They adopt a unique experimental design where the participants in an experiment played the part of individual designers and partook in the design of a physical product conforming to predefined performance objectives. The designers and their artefacts were subsequently scored from idea generation to implementation, and insights were derived from these scores. In another study, Cui et al. (In press) use an innovative field experiment to explore how consumer behavior is impacted by inventory availability at the retailer. Using the lightning deals on Amazon, they downloaded customer and inventory information every 30 seconds and developed metrics to assess customer’s purchasing behavior. They measured inventory availability by percentage of claimed deals. In their field experiment, Cui et al. (In press) create a shock in inventory availability information for a subset of Amazon products and measure cart add-ins after this shock.

BOSCM research in various industrial and service contexts has been evolving. There are specific application domains that have drawn increasing attention. BOSCM studies in healthcare operations is a good example. Some of the related studies have been discussed earlier, but in one of the most recent studies, Song et al. (2018) conduct a field experiment of emergency department employees to investigate how public feedback affects physician’s productivity. In another work, Batt & Terwiesch (2017) study the emergency department as a system of two sequential stages and investigate the response to workload in this department. Staats et al. (2018) provide insights on the role of negative news, past experiences of individuals and greater group experience, and its effects on changing their beliefs in healthcare operations. Using lab experiments they study the impact of negative news by Food and Drug Administration in the US and its impact on the use of two cardiac stents by cardiologists.

It is worth mentioning that we had a total of 28 BOSCM articles in our pool that did not necessarily belong to any of the OSCM contexts discussed in this chapter. These articles mostly include literature reviews, commentaries, and introduction to special issues. An additional 6 papers were categorized in none of the groups which were pertinent to learning and teaching in OM (Lovejoy, 1998; Machuca, 1998), knowledge acquisition (Hora & Klassen, 2013), knowledge sharing (Siemsen et al., 2007), transport (Mak et al., 2018) and safety (de Koster et al., 2011). Appendix A (Tables A1-A2-A3) shows supplementary information on the frequency of publications for data collection methods per operations context, and frequency of operations context and research and data collection methods per journal. The row ‘Other’ in Table A3 refers to the above-mentioned 28 papers.
5. Discussions and Future Research Directions

The field of BOSCM continues to mature, and this review has documented the emergence of several distinct research domains within the field. Better integrating human behavior into our understanding of operational contexts continues to be an exciting avenue for research. Providing advice with respect to structuring and framing decision making – both in day-to-day as well as in strategic contexts – is critical for implementation and practice. As a final post-hoc assessment of the ongoing influence of BOSCM in advancing the operations contexts discussed in section 4, we asked 10 of the well-cited authors in the field (based on citation counts and number of publications) to provide us with their assessment of the key BOSCM topics, in particular the opportunities for future research in each of those contexts (see Appendix B for the survey questions and the Acknowledgment section for a list of survey respondents). The discussion in this section is informed by the results of this survey.

Albeit a small sampling of researchers, likely biased by their own predilection preferences, we do find some consistency across authors questioned. Perhaps not surprisingly, SCM, Service Operations and Auctions were considered as the most popular and fastest evolving domains. More interestingly, views of the importance of Project Management vary considerably from slightly important to very important. This reinforces past anecdotal suggestions that interest in projects as a unit of analysis is somewhat divided in this community, as well as in OM and SCM in general. The surveyed researchers also shared with us their opinion about the most important and challenging topics in the field of BOSCM. Some of key topics are being discussed here.

From this inquiry, it is clear that decision making in practice continues to be heavily influenced by human judgement, even with regards to highly automated and supposedly objective systems. There is a human element that links data to decision making, and documenting and better understanding this human element is a key objective for research in BOSCM. David Ferruci, IBM’s lead in the creation of WATSON, views the future of decision making as a combination of human judgment and algorithms (Tetlock & Gardner, 2015). It is well known that, in practice, algorithms in inventory management, revenue management and forecasting often rely on human interventions to allow correcting for their inherent incompleteness (van Donselaar & Gaur, 2010; Kremer et al., 2011; Kremer et al., 2016). In other operational contexts such as project management, practice is almost entirely dependent on human judgment since relevant algorithms tend to have insufficient specificity or adaptability, and hence very limited formal adoption within organizations.
By attempting to bridge the gulf between practical algorithmic efforts and the complex reality of human decision making, BOSCM not only helps us better understand when human biases, heuristics and judgment may not be beneficial, but also when they may (see, e.g, Flicker, 2018; Petropoulos et al., 2018). Further, in contemporary settings, human judgment across a range of managerial settings rarely develops in the absence of some form of information system, be it semi-structured social media content or a fully established decision support mechanism. Viewed holistically, the key question we are now faced with is how such technologies can be structured to allow people to make better decisions, and under what conditions human judgment should be encouraged or discouraged in the decision-making process.

The challenge of pursuing such research can be daunting but is not insurmountable. Due to its emphasis on novel and counter-intuitive findings as well as its background in mathematical modeling, the fields of OM and SCM have faced some challenges in the cross-pollination of their respective research. What we refer to as the combined research efforts in BOSCM, in contrast, have started to develop a tradition of replication and academic dialogue. A good example is the area of prospect theory in newsvendor research. The original research by Schweitzer & Cachon (2000) ruled out prospect theory as an explanation of newsvendor ordering behavior observed in the laboratory. This sentiment is later echoed by (Nagarajan & Shechter, 2014). However, more recent research points out that this conclusion was based on a specific assumption about the reference point (Long & Nasiry, 2015). This insight has in turn spurred the discussion as to what determines the reference point in newsvendor decision making (Uppari & Hasija, 2018), which is a discourse that is not only relevant to BOSCM, but to our understanding of judgment and decision making in general. We hope that the field of BOSCM maintains and extends this tradition of academic discourse, replication and building upon each other’s work. Hopefully, researchers will also learn to incorporate and value multiple alternate methods into their replication attempts, and joint methods to assist in triangulation and continued discourse.

One key outcome of BOSCM research is the generation and testing of behavioral models (i.e., descriptions of human behavior in operational contexts that allow deviations from rationality). Once the community established consensus on such models, these behavioral models can in turn inform analytical and optimization studies as well as empirical field research. One of the oldest such models is the state-dependent service rate framework by Schultz et al. (1999), which has led to applications in healthcare (e.g., Ke & Terwiesch, 2009) as well as in retail operations (Shunko et al., 2018). Bendoly et al. (2015) further describe a variety of complex conceptual model-forms and phenomena consistently reinforced by empirical observation. A particularly recent example of
behavioral model establishment is the mental sampling model by Tong & Feiler (2017) which may be applicable to many OM contexts as well.

One way of framing the contribution of BOSCM to the field is to examine a core textbook in OSCM, and to compare which of the chapters in the book have started incorporating or could incorporate essential findings from BOSCM. Along several areas – from forecasting, to inventory management, production planning, supplier selection, contracting, service operations and revenue management – the advances to the field originating from BOSCM are clear. In other areas, BOSCM has so far made little impact. For example, very little is known about the behavioral aspects of task scheduling and sequencing, and behavioral research has only recently started shedding light on this area (Ibanez et al., 2018). In another example, work has started to shed light on the individual productivity implications of task assignment in a warehousing context (Batt & Gallino, 2018). In these examples, researchers explore how people behave in a particular operational context, establish empirical rules that describe their behavior, and then develop algorithms or procedures that incorporate these rules of behavior to optimize system performance.

We believe that this framework – obtaining empirical individual level data on an operational context, empirically establishing behavioral rules, and then using these to optimize performance in the operational context – is a very successful and useful approach for research in behavioral operations to extend the reach of BOSCM. Some areas that so far have not been explored include, for example, facility/work layout, quality/reliability management, as well as sales & operations planning. The latter topic, particularly, is a context that is strongly influenced by human judgment, and thus should provide ample opportunity to unearth behavioral rules and create a process that will account for such rules.

While certainly not a comprehensive listing of opportunities, this discussion aimed to provide food for thought, particularly for new researchers to the field. These insights and directives are related to a variety of operations contexts including decision support systems, forecasting, innovation, supply chain performance, buyer-supplier relationship, service operations, capacity management, sustainable operations, and disruptive technologies. They are also highly amenable to mixed method approaches, and likely to spur further discussions in these areas. It is our hope that these ideas find fertile ground in the years to follow, and that they and their inquiries fuel the further evolution of both BOSCM as well as the practical relevance of its associated fields.
Acknowledgment

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Flicker, B. (2018). Managerial insight and optimal algorithms. Working paper, McDermott Graduate Fellow and Doctoral Candidate in Operations Management Jindal School of Management University of Texas at Dallas, U.S.A.


[https://www.nature.com/articles/nature03607#supplementary-information](https://www.nature.com/articles/nature03607#supplementary-information).


### Appendix A  Classification Data

#### Table A1  Research and data collection methods count per operations context (1981 – June 2018)

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<th>Procurement and auctions</th>
<th>Service operations</th>
<th>Project management</th>
<th>Revenue management</th>
<th>Forecasting</th>
<th>Capacity management</th>
<th>Quality management</th>
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### Table A3 Operations context count per journal (1981 – June 2018)

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*Note: The operations context ‘Other’ refers to literature review papers, commentaries, and introduction to special issues as well as 6 additional papers (total 28 articles)*
Appendix B  Survey of BOSCM topics and future research areas

Dear colleague,

We are completing a systematic review of the literature of Behavioral Operations and Supply Chain Management. Our literature mapping and citation analysis of the published papers identified the following research topics.

1. Supply Chain Management
2. Inventory Management
3. Procurement and auctions
4. Service Operations
5. Project Management
6. Revenue Management
7. Forecasting
8. Capacity Management
9. Quality Management
10. New Product Development
11. Production Management
12. Process Improvement

We are now approaching some of the prolific authors in these areas to ask them about the significance of each topic and future directions of the field. Our review identifies you as one of the prolific authors; hence, I am writing to request your responses to the following questions.

1. Based on the potential for future contributions, how critical you think each topics is? Please use a 1-5 scale, 5 being “most critical” or “greatest potential”.
2. What are the most important and challenging research topics in the area of your expertise? Please provide as much details as you can describing potential research directions in your area of research.

We appreciate the time you put into this and look forward to your input.

Kind Regards,

Signature