THREE ESSAYS ON TEXT ANALYTICS
& BEHAVIORAL OPERATIONS MANAGEMENT

by

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ABSTRACT

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My dissertation is about the use of textual analytics in the field of operations management and behavioral operations management. My first chapter analyses the growth of the area of operations management over the past 21 years using a combination of Author Co-Citation Analysis, topic modeling, and term co-occurrence maps. The results indicate that the field of operations management has evolved considerably over the past twenty-one years with the introduction of new topics such as behavioral operations management, healthcare operations management, knowledge-based capabilities, etc. Based on the findings of my first paper, my second and third chapters were developed. My second chapter is an experimental behavioral operations management paper that investigates the effect of social stress on individuals in an operations setting. The results indicate that while social stress did not have a significant impact on performances, learning moderated the negative effect of social stress on order quantity adjustment. My third chapter focuses on the use of textual analytic techniques to measure knowledge relatedness between the firms involved in "Mergers & Acquisitions" and relate it with the success or failure of the M&A transaction and financial returns of the firms. Specifically, cosine similarity was used to measure the knowledge relatedness between the acquirer and target and correlated with the financial performance of the acquirer and target. While cosine similarity was not helpful in predicting the M&A transaction being success or failure, there was considerable evidence for the positive post financial performance of the acquirer in the short term for M&A transactions with higher cosine similarities.

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Introduction

My thesis aims to integrate the use of bibliometric, advanced textual analytics techniques, strategic management, and economic concepts into the field of Operations Management. By drawing from different research domains, I aim to contribute to the field of Operations Management by traversing beyond the traditional realm.

My first chapter is an intellectual inquiry into the evolution of the field of Operations Management over the past 21 years. I employ Author Co-Citation Analysis (ACA), along with topic modeling and term co-occurrence network to analyze the key knowledge groups with their evolution, and seminal authors in the field of operations management over the past 21 years. The analyses and subsequent results shed light on how the field of operations management has evolved over the past 21 years. The use of topic modeling and term co-occurrence network reinforces the use of advanced text analytics-based measures, and the results indicate that a wide variety of topics including behavioral operations management and high technology acquisitions are gaining traction. Based on the results of my first chapter, the second, and third chapters were developed. My second chapter is a behavioral operations management paper that incorporates experimental economics, and the third chapter utilizes textual analytic techniques to measure the knowledge relatedness between firms related in mergers and acquisitions and relates it with post acquisition performance.

My second chapter is an experimental investigation into how social stress impacts inventory decision making managers. Taking into account the great impact the field of behavioral operations management has had since the emergence of the seminal paper by Schweitzer &

Cachon (2000) and confirmation from the findings of my first chapter, my second chapter is a behavioral operations management paper that incorporates a standard economic experiment to answer whether social stress improves or deteriorates performance of individuals in an OM setting. Behavioral operations management has used economic experiment-based settings to study how humans react to different operations management game scenarios. Traditionally, early researchers in this domain have assumed homogeneity in decision making across individuals. I contribute to the advancement of research in individual heterogenous decision making under different operations management game scenarios. Specifically, social stress was used to explain variability in inventory decision making utilizing the newsvendor problem as the operations management game. I find significant interaction between social stress and learning on order quantity adjustment in the positive direction. My research has implications at the managerial level for improving individual performances under an OM setting.

My third paper builds on my use of advanced textual analytic techniques in my first paper to answer novel research questions. I use the field of Mergers & Acquisitions (M&A) in 3 high technology industries to test if knowledge relatedness between acquirer and target can predict the transaction being completed or withdrawn, and whether higher knowledge relatedness is related to better financial performance of the acquirer post-acquisition. I utilize cosine similarity as a measure of knowledge relatedness between acquirer and target and use Cumulative Abnormal Return (CAR) as a measure of financial performance. My research findings have implications for investors looking to invest in acquirers' post-acquisition in the short-term, as cosine similarity positively impacts the financial performance of the acquirer in the short term.

By utilizing the 3 chapters, I contribute to my theme of the use of textual analytics techniques in operations management research, and behavioral operations management. By incorporating such novel research techniques, I aim to contribute to the literature of OM and enhance the understanding of scholars in the use of such techniques.

Methodology

As my thesis is split into 3 different chapters, I utilize a variety of statistical techniques to answer my research questions.

In my first chapter, I perform factor analysis, Multidimensional Scaling (MDS), and Pathfinder Analysis on the Author Co-Citation matrix to extract the different factors in operations management research and understand the intellectual evolution of the operations management field over the past 21 years. I complement my findings with term co-occurrence maps using the textual analytic tool VOSviewer (van Eck & Waltman, 2011), and topic modeling using Latent Dirichlet Allocation (LDA).

In my second chapter, which is an experimental paper, I have employed linear regression to check for the effect of social stress on average expected profits of individuals. As the individuals play the newsvendor game over a period of 100 rounds, a panel data was formed which was suitable for running a time-lag random-effects model. The random-effects model was utilized to check for the effect of demand chasing, learning, and other interesting interaction effects with social stress, event load, CRT score etc.

In my third chapter, I employ a combination of parametric and non-parametric tests to answer my research questions. For the robustness check, the CAR of the target was compared against acquirer using a combination of Paired sample t-test, and Wilcoxon signed-rank test. For testing the first hypothesis that the cosine similarities within the same industry pair are higher than that of pairs across industries, the cosine similarities of within the same industry were compared against cosine similarities across industries using a combination of independent sample t-test, and Mann Whitney U test. Since status was a binary variable that could take either 0 for withdrawn or 1 for completed, a binary logistic regression was deemed appropriate to test the second hypothesis that M&A transactions with higher cosine similarity can lead to higher chance of success using status as the dependent variable, cosine similarity as the independent variable and Number of Employees / Sales for both the acquirer and target as controls. The third and final hypothesis that the Cumulative Abnormal Return of the acquirer 1 year post the announcement date will be higher for acquirer-target pairs with higher cosine similarities was tested utilizing the node-level regression procedure in the network software UCINET where the dependent variable was the Cumulative Abnormal Return and the independent variable was the cosine similarity between the acquirer and target. The number of Employees / Sales for both the acquirer and target were utilized as control variables in the node-level regression model.

The statistical techniques used in my thesis were chosen based on the variables in the dataset and the research questions. All statistical techniques employed in my thesis were validated by a team of statistical experts.

Chapter 1.

Analyzing Operations Management Literature through an Author Co-Citation & Textual Analytics Lens

Abstract

The field of operations management has undergone a significant evolution over the period 1997-2017. This paper analyzes the operations management literature through a textual analytics lens to capture the core of this evolution. Author Co-Citation analyses answer vital questions such as influential authors and seminal papers. The comparison of topics across different periods from Author Co-Citation Analysis and topic modeling gives us an idea into the intellectual evolution of the field of operations management over the past two decades. My analyses show that the area of operations management has been growing in the past two decades, as indicated by the increase in co-citation topics over the three different periods studied. While some research topics in the field of operations management have remained significantly important over the periods measured, the topics have evolved from mainly a manufacturing perspective to more diversity of topics such as the incorporation of different disciplines such as behavioral economics, healthcare operations. My paper analyzes the differences in the three-time periods analyzed deeply and provides an agenda for future research.

Keywords: Topic Modeling, LDA, Author Co-Citation Analysis (ACA), Principle Component Analysis (PCA), Multidimensional Scaling (MDS), Term Co-Occurrence Map.

1. Introduction

Frederick W Taylor's pioneering principles of scientific management (Taylor, 1911) can be considered to an early starting point in the field of operations management. Since then, Operations management has come a long way. A more recent definition of Operations management would be "the design, operation, and improvement of the systems that create and deliver the firm's primary products and services" (Jacobs & Chase, 2013). Over the years, Operations management has grown into a more mature discipline and can be classified as one of the functional fields of business along with finance, marketing, and sales (Jacobs & Chase, 2013). Moreover, we can observe that research in the field of operations management has gained a lot of momentum in the past two decades, and operations management is now considered to be a strong, and well respected academic discipline (Pagell & Krause, 2004).

The research agenda for my paper is three-fold:

(i). To identify the key topics in the operations management research literature and their evolution over the past two decades.

(ii). To determine the most influential authors in the field of operations management research over the past two decades.

(iii). To determine the critical knowledge groups in the operations management research literature and their evolution over the past two decades.

The data used for my study is the 14672 research articles from six highly ranked and respected journals in the field of operations management for the period 1997 to 2017. Author Co-Citation Analysis (ACA) along with Principal Component Analysis (PCA), Multidimensional Scaling

(MDS), Key Word Analysis, and Topic Modeling were employed to answer my research questions.

Section 2 begins with the literature review and motivation for this research. Section 3 explains the data. Section 4 explains the method, analysis, and results. Section 5 provides a summary of the conclusion and talks about venues for future research.

2. Literature Review & Motivation

It is difficult to trace the exact origins of the field of operations management (Chopra, Lovejoy, & Yano, 2004). One can argue that one of the first works that lead towards the introduction of the OM field can be the scientific management concept by Frederick W Taylor (Scranton, 1998). Taylor's Principles of Scientific Management dealt with the development of true science, scientific selection of the worker, scientific education and development of the worker, and friendly cooperation between management and the workers (Taylor, 1911). Attempts into using optimization techniques within the field of OM came in the early 20th century, such as the Economic Order Quantity (EOQ) model (Erlenkotter, 1990), while the 1960s and '70s were the time period when there was a significant understanding of different problems that can be encountered in operations, planning, and control, along with the use of optimization techniques (Loch & Wu, 2007).

The first issue of the Journal of Operations Management and the International Journal of Operations & Production Management came out in the year 1980. Since the first issue of the Journal of Operations Management, more journals have been publishing research articles in operations management.

There are numerous ways to examine previous research literature on a particular topic or field. Previous studies can be reviewed using quantitative analysis, qualitative methods, or both (Dobrzykowski, Saboori Deilami, Hong, & Kim, 2014).

Literature and content analysis has been used by previous researchers to summarize the research done in various academic disciplines, including operations management. An early paper in this direction was the seminal paper by Chase (1980), in which literature content analysis from leading journals was used to study the current state of research, and layout a framework for future research in the upcoming field of operations management. Amoako-Gyampah & Meredith (1989) used literature content studies to compare results from Chase's paper and evaluate the state of operations management research from the years 1982 to 1987. OM research done in the 1990s was summarized by Pannirselvam, Ferguson, Ash, & Siferd (1999). Sower, Motwani, & Savoie (1997) surveyed OM professionals to identify classic authors and publications in the field of OM. A recent example of qualitative analysis is the study by Singh, Kurian, & Napier (2018), in which the authors explored the application of The Dynamic Capabilities View (Teece, Pisano, & Shuen, 1997) in the field of supply chain and operations management.

Bibliometric analyses such as citation and co-citation use the number of citations, i.e., how many times the articles have been cited, instead of relying on qualitative methods. Citation analysis uses the number of times an article is cited, whereas co-citation uses the co-occurrence of citations among two articles. Citation analysis is based on the understanding that articles which are heavily cited are considered to be more influential in comparison to less cited papers (Culnan, 1986). Citation/Co-citation studies can give great insights into the genuinely influential articles, and authors in a particular field. Co-citation studies, in particular, can provide the crucial topics, authors, journals, and research methods that are central and tangential to the area, along with their evolution over time (Pilkington & Meredith, 2009).

Citation and Co-Citation techniques have been employed in numerous disciplines to identify knowledge groups, influential authors, influential articles, and give an overview of the intellectual structure of the field. Kärki (1996) used author co-citation analysis to examine the sociology of science literature. Nerur, Rasheed, & Natarajan (2008) employed author co-citation analysis to study the intellectual structure of the field of strategic management. In the area of information systems, Dwivedi & Nerur (2017) used citation analysis along with text mining, and topic modeling to examine the conceptual foundations of the field of business analytics. Wang et al. (2016) used citation/co-citation analysis in conjunction with principal component factor analysis to identify the important papers and identify the research themes in cloud computing research in the IS discipline.

In the field of operations management, Pilkington & Liston-Heyes (1999), studied IJPM citations to plot the five subfields in OM which were named: Japanese Manufacturing, Manufacturing Strategy Developers, Manufacturing Strategy Proposers, Performance Measures, and Best Practise. It was also found that European and North American researchers have different importance for each plotted subfields.

Pilkington & Fitzgerald (2006) determined changes in the OM field's categories over ten years. The main changes were the inclusion of two groups, Resource-Based View, and Theory Building. Some emerging topics such as lean, qualitative methods, supply chain were also identified. A more recent venture into citation/co-citation analysis in the field of Operations Management is the study by Pilkington & Meredith (2009), who used citation data from 3 OM only journals: Journal of Operations Management, Production and Operations Management Journal, and International Journal of Production & Operations Management to analyse the intellectual structure of the OM field from the years 1980 to 2006. The unit of analysis in their study was the three journals used. From the principal component factor analysis used, five factors were identified: Manufacturing Strategy, Quality & Metrics, Statistical Methods, Process Design, Services, Flexibility, Qualitative Methods, Supply Chain, Prod/Serv Innovation, Resource-Based View, Measures/BSC. They also found that most references came from books, followed by seminal journal articles.

Even though citations can aid to detect paradigm shifts (Sircar, Nerur, & Mahapatra, 2001), and in understanding evolution of disciplines (Culnan, 1986), they have some limitations (Dwivedi & Nerur, 2017) as well. One of the primary constraints is that citations do not take into consideration the context in which they appear in articles. Moreover, the content of articles is neglected when citations are used to draw the intellectual structure of a field (Balijepally & Nerur, 2015). The fact that citation/co-citation analysis mainly relies on seminal authors or documents can also be a drawback (Zhao & Strotmann, 2007).

My primary motivation for this research is to address the shortcomings in previous OM qualitative, and citation-based studies to study the intellectual structure of the field over the past 21 years (1997 to 2017). The period of 1997 to 2017 was chosen as it is an exciting period to analyze the area of operations management and 21 years is a long enough period to account for the changes in technology, economy, and other factors that can contribute to the growth of a particular field. Moreover, mapping out the intellectual structure of an area needs to be done every 10 to 15 years, as the time frame of 10 to 15 years is enough for significant changes to take place in a field (Pilkington & Meredith, 2009).

To minimize the limitations of citation / co-cocitation analysis and to take into consideration the content of articles, I use ACA along with topic modeling and keyword analysis on journal articles as the unit of analysis to map the evolution of the field of Operations Management over the past two decades. The past two decades has been an exciting period for researchers worldwide, with the significant advancements in technology, and abundant data to work with. A lot of research has done in the field of operations management over the past two decades. A person who is new to the area of OM can have difficulties going through the vast amount of literature. From the research done in this paper, I aim to make it easier for such newcomers in the field by giving them a birds' eye view of the operations management literature over the past twenty years. Experts in the field of OM too can use this research to bolster their existing knowledge of research in OM. The years 1997 to 2017 also capture the research done in the new millennium. The new millennium with introduction of new technologies, the proliferation of the use of the World Wide Web is an exciting time for such kind of research to be done.

The use of bibliometric analyses has several advantages over qualitative studies, such as that of being quantifiable and the avoidance of potential subjective biases. My research aims to bolster and complement current studies that analyze the intellectual growth of operations management.

3. Data

Abstraction, which is known as the act of abstracting is a natural process that helps one cope with the complexities in the real world. An abstract is usually found at the beginning of a research article to provide a synopsis or summary of the research article and thereby help the reader understand the purpose and main results of a paper (Blake & W. Bly, 1993). One way to collect abstracts in any field from a citation indexing service is the use of keywords that one deems to be appropriate. However, there are many complications in the use of keywords to collect abstracts (Kapoor et al., 2017). For example, the use of the keyword "Operations Management" filtered from the year 1997 to 2017 in the database Web of Science yielded 101135 abstracts. Of these abstracts, some were regarding fuel cell durability, and medical laboratory research, none of which are related to Operations Management.

Cited References that are found from the bibliography or list of references of an article are very imperative in the evolution of literature in a field. The cited references include references from any journal article, book, paper, dissertations, etc. Both Abstracts and Cited References were obtained from the citation indexing service Web of Science (WOS). Abstracts were used as input data for topic model and term co-occurrence maps. Cited references were used as input into Author Co-Citation Analysis.

3.1. Journal Selection

Given the multiple issues with using keywords, a manual search using a basket of top Operations Management Journals was found to be more appropriate. The unit of analysis is the research articles resulting from the basket of journals. Since the selection of journals has a considerable impact on the results obtained, a rigorous and multistage approach was used. Among the various ways to measure the quality of a journal, opinion surveys and citation studies are well regarded procedures commonly used in different domains such as in finance (Oltheten, Travlos, & Theoharakis, 2003), information systems (Barnes, 2005), management (Podsakoff, Mackenzie, Bachrach, & Podsakoff, 2005), marketing (Guidry et al., 2004), etc. In opinion surveys, experts in a field are surveyed on their opinions of the perceived quality of a journal and its relative importance concerning that field of study. The survey results are then consolidated to get the journal ranks. In the field of operations management, there have been many opinion survey studies conducted in academic conferences. For example, Barman, Hanna, & LaForge (2001) ranked the perceived importance and quality of a set of POM journals by surveying the United States-based members of POMS (Production and Operations Management Society). Theoharakis, Voss, Hadjinicola, & Soteriou (2007) emailed surveys on the perceived quality of OM related articles published by the journals to 9674 researchers around the world and found that the journal rankings varied significantly according to the region of the world, and the self-classification of researchers as empirical or modeling based.

Citation studies are based on two approaches, as explained in Goh, Holsapple, Johnson, & Tanner (1996). The first approach which analyses data published in the Social Science Citation Index (SSCI) is not suited for OM based journals, as some of these journals are not indexed in the SSCI (Petersen, Aase, & Heiser, 2011). The second approach involves selecting a list of base journals and collecting citation data manually for all OM based articles within that list (Petersen et al., 2011). The first citation analysis in the field of OM was conducted by Vokurka (1996) in which the citations from 1992 to 1994 were collected from 3 base journals: *Decision Sciences (DS), Journal of Operations Management (JOM), and Management Science (MS).* The resultant citation data was used to publish rankings of OM journals. Goh, Holsapple, Johnson, & Tanner (1997) used citation data from Journal of Operations Management (JOM), International Journal of Production Research (IJPR), and International Journal of Operations & Production Management (IJPM) for the years 1989 to 1993 to publish their list of rankings.

Petersen et al. (2011) employed meta-analysis to consolidate the results from 5 different citation and opinion studies and publish their rankings of OM journals. Using the meta-analysis technique alleviates the problems from biases that arise from individual studies. Petersen et al. (

2011) utilized the meta-analysis technique used by Rainer & Miller (2005) to study MIS journals.

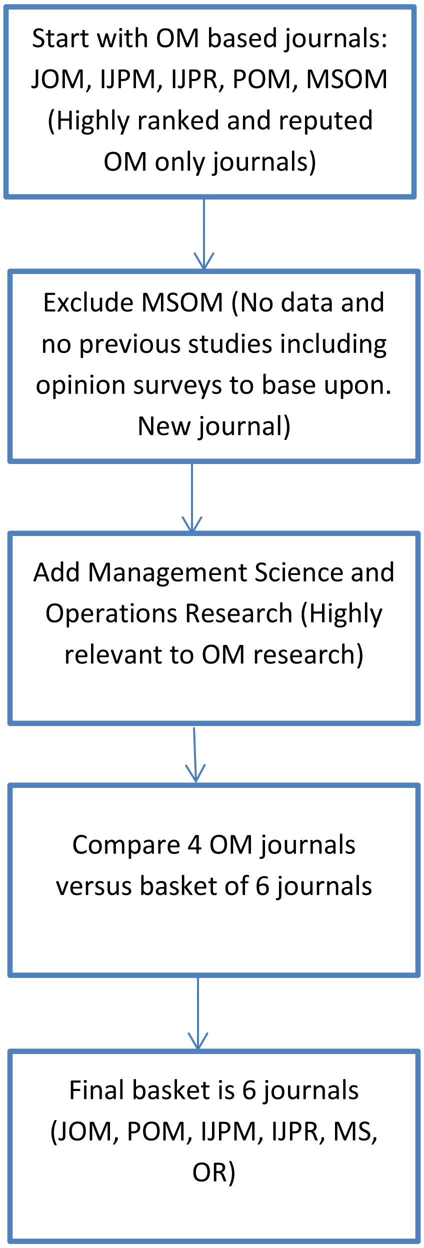
For this paper, a combination of opinion surveys, citation studies, and the meta-analysis results provided by Petersen et al. (2011) were used for selecting journals. Table 1 outlines the journal rankings from different studies, and table 2 describes the various steps involved in the process of journal selection. Opinion surveys were included as opinions provided by human experts are considered invaluable and hence should not be neglected. The use of citation studies combined with the use of opinion surveys and journal ranking lists provides a valuable mix of qualitative and quantitate studies to base the journal selection on.

Table 1. Journal Rankings Comparison for Journal Selection (Qualitative vs. Quantitative)

Number	Journal	OM based	Financial Times	UT Dallas	Vokurka rank	Petersen Rank	Theoharakis Survey rank	Barman Survey Rank	ABDC ranking
1	JOM	✓	✓	✓	5	2	7	3	A*
2	POM	✓	✓	✓	N/A	5	9	5	A
3	IJPM	✓			12	4	20	16	A
4	IJPR	✓			2	11	15	11	A
5	MS		✓	✓	1	1	1	1	A*
6	OR		✓	✓	3	14	2	2	A*
8	MSOM	✓	✓	✓	N/A	N/A	N/A	N/A	A

The list of 8 initial journals chosen for comparison is shown in Table 1. The table indicates whether a journal is OM based or not, whether it is listed in the Financial Times list and UT Dallas list or not. Vokurka rank is the rank obtained from the Vokurka citation study Vokurka (1996), Petersen rank is the meta-analysis rank derived from the Petersen study (Petersen et al., 2011). Theoharakis Survey rank and Barman survey rank are the ranks obtained from opinion survey studies. The last column in Table 1 denotes ABDC (Australian Business Dean Council) journal ranking, which is used by business schools worldwide for measuring the quality of business journals. The initial list of journals was compiled in such a way that each journal should be mentioned in at least 3 of the ranking measures, and that each journal should be ranked A or higher in ABDC ranking. ABDC awards the A ranking to Near-Elite journals and A^* ranking to elite journals.

Table 2. Journal Selection Flowchart



The first step in journal selection (Table 2) is to start with purely OM based journals. Based on the studies by Pilkington & Meredith (2009) and Petersen et al (2011), *Journal of Operations Management (JOM), International Journal of Operations & Production Management (IJPM), International Journal of Production Research (IJPR), POM (Production & Operations*

Management), and MSOM (Manufacturing & Service Operations Management) were selected as the base OM journals to start with. From this list of journals, MSOM was excluded. There were 3 reasons as to why MSOM was excluded: The first reason was that as it is a newer journal with its first issue released in 1999, the second reason was that there were no previous citation or opinion studies that used MSOM, and the third reason was that the Web of Science database does not index MSOM articles.

Since the field of management science and operations research have significant importance in the field of operations management as indicated by different studies (Petersen et al., 2011), the next step in journal selection was to add the journals *Management Science (MS) and Operations Research (OR)* and to check if adding these 2 journals has any contribution compared to the list of 4 purely OM based journals.

To compare the 4 OM based journals versus the 6-journal list including MS and OR, the co-citation clusters, the term co-occurrence clusters from the software VOSviewer (van Eck & Waltman, 2011), and the Principal Component Analysis (PCA) clusters for the four journal list were compared versus six journal list. A detailed explanation of Author Co-Citation (ACA) matrices and related methodologies can be found in the ACA section.

Table 3. 4 Journal vs. 6 Journal Filtering Criteria (Co-Occurrence & Co-Citation)

Min number of citations	Min number of keyword Co-Occurrence	Keyword Terms	Co-Citation Matrix
4 journal: 250	4 journal:100	298 (0.6*496)	67*67
6 journal: 320	6 journal: 143	298 (0.6*496)	67*67

The minimum number of citations was set for both the list of 4 journals and six journals to get similar co-citation matrix for comparison purposes (Table 3). Using the co-citation matrix obtained from the 4 and six journal list, co-citation clusters were obtained using the software VOSviewer and by Principal Component Analysis (PCA) using the software SPSS (Table 4).

Table 4. 4 Journal vs 6 Journal Clusters Comparison (Co-Citation & Co-Occurrence)

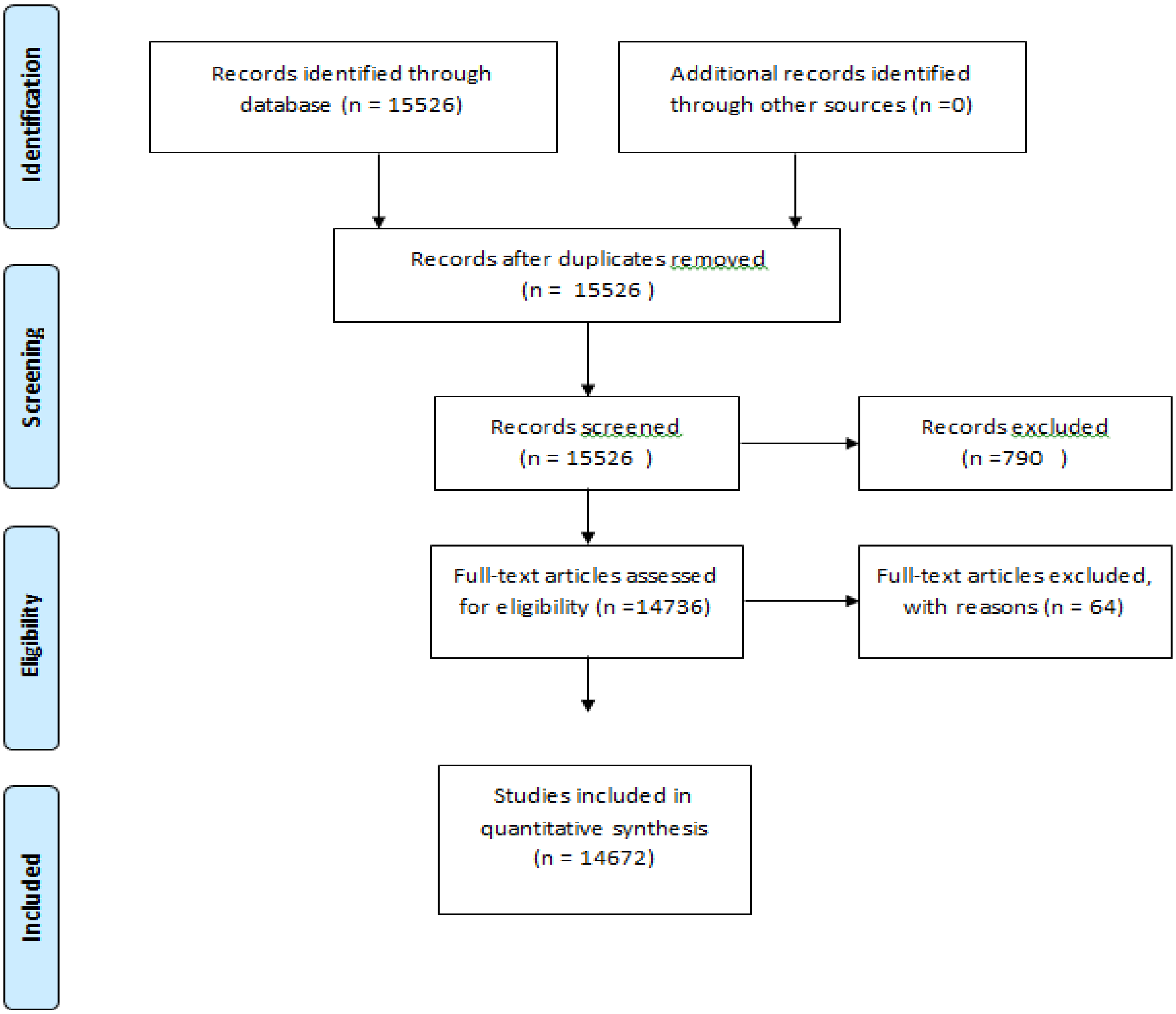
4 journal Co-Cite clusters	6 journal Co-Cite clusters	4 journal term co-occurrence clusters	6 journal term co-occurrence clusters	4 journal PCA clusters (from 67*67 matrix)	6 journal PCA clusters (from 67*67 matrix)
4	5	3	3	11	14

Even though the term co-occurrence clusters for both the four journal and six journal list are 3, the number of co-citation clusters from VOSviewer and Principal component analysis was more for the 6-journal basket compared to the 4-journal basket (Table 4). PCA on the co-citation matrix resulted in 14 clusters for the 6-journal basket compared to 11 for the 4-journal basket, while VOSviewer yielded five distinct clusters for the 6-journal basket compared to 4 clusters for the 4-journal basket. As the co-citation matrix was fixed to 67*67 authors, the higher number of co-citation clusters for the 6-journal basket means that there are more distinct research topics of interest in the 6-journal basket as compared to the 4-journal basket. As a result, the articles reviewed in this study are from the following Operations Management Journals: *Journal of Operations Management (JOM); Management Science (MS); Production and Operations Management (POM); International Journal of Operations & Production Management (IJPM); International Journal of Production Research (IJPR); Operations Research (OR).* From the basket of 6 journals, only peer-reviewed published journal articles were selected from the years 1997 to 2017. The abstracts from these articles form the resultant text corpus.

3.2. Selection of Articles

The Web of Science (WOS) database was used to collect abstracts from the basket of 6 journals. Since the Web of Science indexes proceedings papers, editorial materials, reviews, and corrections, the Prisma Flow Diagram (Moher D, Liberati A, Tetzlaff J, 2009) was used for filtering out the articles. The Prisma Flow Diagram follows a systematic approach comprising of 4 different steps that are developed for filtering articles.

Figure 1. Prisma Flow Diagram for Article Filtering & Selection. Adapted from Moher D, Liberati A, Tetzlaff J (2009)



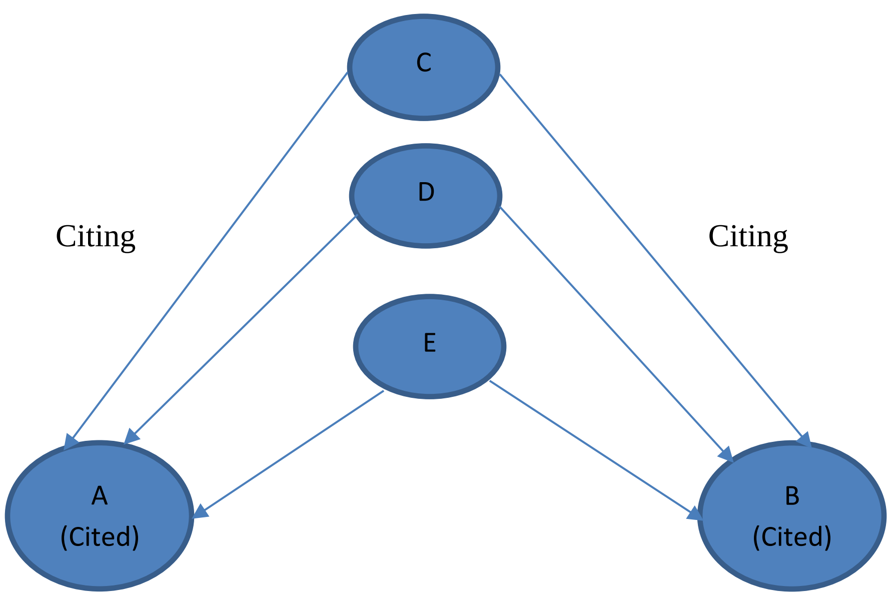
The first step in the Prisma Framework (Figure 1) is the identification in which 15526 articles were identified from the basket of 6 journals. All 15526 articles were included, as no duplicates were not found. In the second step of screening, 790 papers (401 proceedings papers and 389 editorial papers) were excluded, bringing down the total to 14736 documents. In the third step, 64 editorial articles were excluded. The resulting filtering criteria lead to 14672 peer-reviewed journal research article abstracts, which formed the text corpus for my study and hence included in my analysis.

3. Methodology & Results

3.1. Author Co-Citation Analysis (ACA):

Co-citation is a semantic similarity measure, which is similar to bibliographic coupling proposed by Kessler (1963). Co-citation occurs when two documents are cited together by other documents (Small, 1973). For example, if paper A cites both papers B and C, then papers B and C are said to be co-cited. The central premise in co-citation analysis is that if two papers are commonly cited by other articles, then the two documents which are commonly cited are more likely to have a similar research theme. Author Co-Citation Analysis uses the first authors as the unit of analysis.

Figure 2. Author Co-Citation



In Figure 2, authors C, D, and E are citing authors A and B together, which means that Authors A and B are co-cited. Since three authors are citing A and B together, the co-citation index is three here (Figure 2).

ACA as a bibliometric technique has been rising in prominence over the past few decades. ACA has been used in varying contexts such as to explain different subfields in a specific discipline and the inter-relationships between them (McCain, 1983;)Culnan, O'Reilly, & Chatman, 1990) Ponzi, 2002), to evaluate research traditions (Cottrill, Rogers, & Mills, 1989), and to answer the question of whether object-oriented programming represents a paradigm shift or not by studying the conceptual differences between seminal authors in the field of software development (Sircar et al., 2001). Author Co-Citation Analysis offers a fair and empirical form of analysis for studying the growth and development of a field, thus minimizing biases associated with qualitative studies. The use of citation patterns to understand the evolution of an area has been proposed by numerous scholars such as Crane (1972), Weber (1987), White & McCain (1998).

Authors working in a similar field cite one another frequently, and furthermore, their works are commonly cited (co-cited) by other authors working in the same area (Nerur et al., 2008). Authors commonly co-cited by other authors usually tend to work on similar research themes. Identifying the seminal authors in a field and their frequency of co-citations can be used for cluster analysis and factor analysis which help in identifying research themes, complicated social network relationships, and changes of these research themes over time.

3.1.1. Co-Citation Matrix

Co-citation matrix is a co-occurrence matrix which is used as input data to understand underlying structures in documents (Leydesdorff & Vaughan, 2006). Different types of analyses have been performed on the co-citation matrix, which makes it essential in information science (Howard D. White & McCain, 1998). Co-Citation matrix is used as an input into the ACA, and hence, it is imperative to understand what the co-citation matrix refers to.

Symmetrical Co-Citation Matrix:

Co-citation analysis was introduced by Small (1973) in his seminal paper, in which the unit of analysis was cited documents. The co-citation matrices used by Small showed the frequencies of co-citation between documents, and were symmetrical, as the objects in the rows were same as that of the columns, the number of rows and columns were similar, and data of the matrix was symmetrical about the diagonal (Figure 3).

Figure 3. Co-Citation Matrix (Symmetrical)

	Paper 1	Paper 2	Paper 3
Paper 1		10	20
Paper 2	10		15
Paper 3	20	15	

Figure 3 shows a sample Co-Citation matrix with three papers: Paper 1, Paper 2, and Paper 3. Here, Papers 1 & 2 are cited ten times together by other articles, Papers 1 & 3 are mentioned 20 times together by other articles, and Papers 2 & 3 are mentioned 15 times together by other articles.

The concept of co-citation analysis was extended by White & Griffith (1981) to Author Co-Citation Analysis (ACA). They used the first authors instead of papers as their unit of analysis. Therefore, the co-citation matrix for ACA would show authors instead of articles.

Figure 4. Author Co-Citation Matrix (Symmetrical)

	Author 1	Author 2	Author 3
Author 1		10	20
Author 2	10		15
Author 3	20	15	

In Figure 4, papers are replaced with their respective lead first authors. Here, Authors 1 & 2 are cited ten times together by other authors, Authors 1 & 3 are mentioned 20 times together by other authors, and Authors 2 & 3 are mentioned 15 times together by other authors.

3.1.2. Unit of Analysis:

In citation studies, the unit of analysis can be a paper or book (Ramos-Rodrígue & Ruíz-Navarro, 2004), author (Howard D. White & McCain, 1998) (Nerur et al., 2008) or journal (Pilkington & Meredith, 2009). The unit of analysis used here in my ACA study is the first lead author. Authors working on consistent research themes throughout their career over time can be useful in studying the development of a field over time. Typically, authors work on a focus area of research throughout their career, advancing their knowledge and contributing to the field. Thus, by studying the seminal authors in a field, the social networks with other authors and their interrelationships between their works overtime, one can unravel the maturity and advancement of an area. As prior studies (Pilkington & Meredith, 2009) (Ramos-Rodrígue & Ruíz-Navarro,

2004) (Podsakoff et al., 2005) have shown, treating journals or books as a unit of analysis can be useful in answering the questions related to the advancement of a field, employing authors as unit of analysis can complement previous studies such as (Pilkington & Meredith, 2009) and provide new insights into the seminal operations management authors, the interrelationships between authors of operations management and other fields, and the different subfields in operations management.

3.1.3. Selection of Authors:

Authors critical to the intellectual growth of operations management are essential in analyzing the growth of the field of operations management over the period 1997-2017. The 21-year period showcases significant growth and development in the field of operations management. Operations management as an area has borrowed concepts from other areas such as Strategic management, Economics, Marketing, etc. Therefore, author selection was made in a manner such that the lead first authors who are highly cited and influential were chosen from the cited references column in the data set. As ACA studies usually focus on 50-70 prominent authors, authors with only 320 or more citations were used, bringing the author count to 67 famous first authors, which were used for unraveling the key knowledge groups in the past two decades.

Table 5. Selected Authors for ACA

Authors	Citations
Flynn, BB	935
Skinner W	624
Lee, Hl	1250
Hayes, RH	645
Boyer, KK	545
Porter, ME	766
Eisenhardt, KM	716
Narasimhan, R	506
Anderson, JC	524
Ward, PT	337
Roth, AV	373
Cachon, GP	1094
Dyer, JH	521
Ferdows, K	344
Schmenner, RW	357
Podsakoff, PM	419
Womack, JP	530
Swamidass, PM	327
Yin, RK	491
Teece, DJ	459
Hendricks, KB	482
Fornell, C	382
Choi, TY	349
Schonberger, RJ	385
Williamson, OE	444
Handfield, RB	339
Voss, C	340
Kaplan, RS	431
Slack, N	326
Fine, CH	355
Fisher, ML	445
Chase, RB	366
Federgruen, A	612
Chen, F	370
Clark, KB	330
Neely, A	348
Aviv, Y	341
Gunasaekaran, A	417
Graves, SC	438
Bendoly, E	321
Gallego, G	572
Corbett, CJ	356

Simon, HA	324
Zipkin, P	345
Cohen, MA	329
Hopp, WJ	438
Banker, RD	343
Song, JS	328
Kahneman, D	462
Milgrom, P	330
Bertsimas, D	565
Kouvelis, P	322
Charnes, A	368
Chen, X	344
Buzacott, JA	439
Tversky, A	422
Guide, Vdr	473
Chan, Fts	376
Whitt, W	490
Harrison, JM	338
Saaty, TL	415
Baker, KR	340
Fama, EF	378
Kusiak, A	402
Garey, MR	342
Glover, F	385
Montgomery, DC	410

3.1.4. ACA methodology:

Multivariate cluster analysis such as Factor Analysis and Multidimensional Scaling are commonly used in Author Co-Citation Analysis. Multidimensional Scaling (MDS) and cluster analysis were the techniques employed by Small (1973) and White & Griffith (1981) in co-citation analysis, while White & McCain (1998) applied factor analysis as well.

My agenda for Author Co-Citation Analysis:

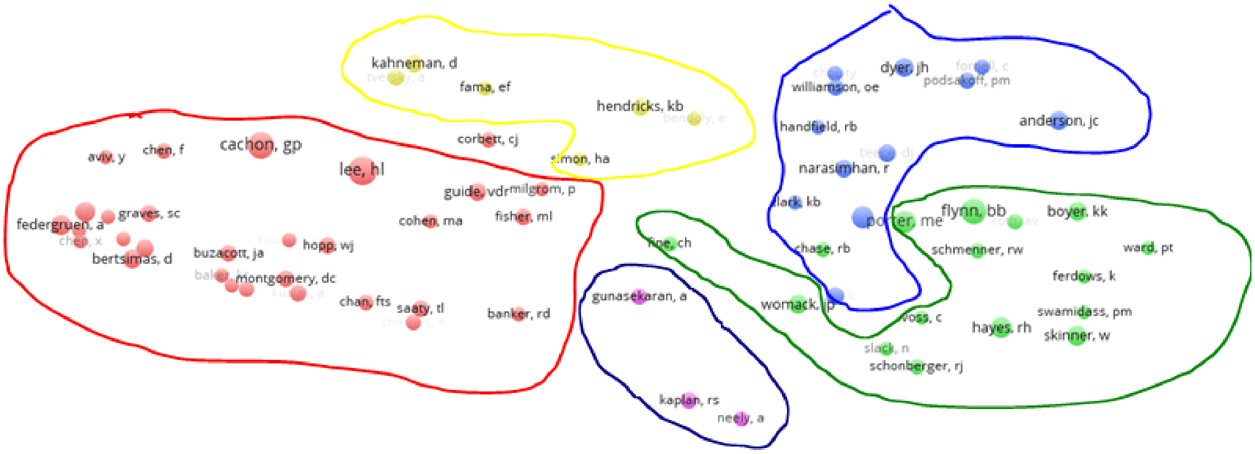
1. To provide an overview of research topics in the field of operations management over the past two decades.
2. To analyze the intellectual growth of the topics, as explained from the Author Co-Citation clusters in the field of operations management over the past two decades.

The following steps were followed for ACA as outlined in (McCain, 1990a) and (Nerur et al., 2008):

- Identify highly cited seminal authors
- Get co-citation counts for each author pair
- Compute matrix of raw co-citations and matrix of Pearson's correlations
- Perform factor analysis to identify subfields
- Perform Multidimensional scaling (MDS) to map author proximities graphically.
- Conduct Pathfinder analysis to explain network relationships between authors.
- Finally, interpret the results.

For my first ACA agenda, the software VOSviewer (Van Eck and Waltman, 2011) was used. From the 14672 articles, only the first authors, with a minimum of 320 citations were considered, to focus on mainly the seminal authors consistent with previous studies (Nerur et al., 2008). The threshold of 320 citations bought the co-citation matrix to 67*67, which reflects 67 seminal authors from the basket of 6 journals. From the co-citation matrix, the cluster analysis performed in VOSviewer identified five distinct ACA clusters (Figure 5).

Figure 5. Author Co-Citation Clusters (VOSviewer)



Cluster 1, Operations Strategy:

The authors in this cluster have contributed towards research in Operations Strategy. Prominent names in this cluster include Robert Hayes, Barbara Flynn, and Roger Schmenner. Strategic management gurus such as Michael Porter, known for Porter's five forces analysis (Porter, 1979) are also featured in this article. Other prominent authors in Cluster 1 include scholars such as Kenneth Boyer, who integrate strategic management concepts in the field of operations management. The research articles from these authors highlight the interface between strategy and operations management. This cluster is of great importance in the research for the field of operations management, as operations management researchers draw theories from the field of strategic management to provide explanations to answer research questions.

Cluster 2, Operations Management & Marketing:

Cluster 2 is dominated by authors whose research expertise lie in the area of Sustainability in Operations, green supply chain management. Some authors in this area of research include James C Anderson, R Narasimhan.

Cluster 3, Operations Research & Behavioral Operations Management:

Cluster 4 showcases research done in two fields: operations research, and the relatively new field of Behavioral Operations Management. Some prominent authors from the operations research field seen in this cluster include Gerard Cachon and Guillermo Gallego. Cachon is also known for his pioneering work in the field of behavioral operations management, such as the seminal newsvendor paper (Schweitzer & Cachon, 2000), which demonstrated that people systematically deviate from the optimal order quantity in the newsvendor problem, along with some explanations for this deviation. Behavioral operations management is the application of economic concepts such as risk aversion and loss aversion, along with mathematical modeling to explain the behavior of people under certain operations management settings.

Cluster 4, Economics & Psychology:

Cluster 4 features prominent psychologists Daniel Kahneman and Amos Tversky, well known for their work on prospect theory (Kahneman & Tversky, 1979), economist Eugene Fama best known for his work on the Fama-French three-factor model (Fama & French, 1993). The other prominent authors in cluster 4 include Kevin Hendricks and Elliot Bendoly.

Cluster 5, Operations Management & Technology:

Authors in this cluster are well known for their research in the integration of operations management with technology and innovation. Prominent authors in Cluster 5 include Angappa Gunasekaran and Andy Neely.

3.1.4.1. Co-Citation data for three periods:

To answer my second research agenda in ACA, the period of 21 years (1997- 2017) was split into three different periods of 7 years each, as done in the Ramos-Rodrígue & Ruíz-Navarro (2004) and Nerur et al. (2008) study. The list of cited references was compiled from the CR column available in the Web of Sciences database and split into three different periods: 1997-2003, 2004-2010, and 2011-2017. The CR column includes all the works published by the author in any publication outlet. As author co-citation is said to have occurred when an author commonly cites 2 authors, the frequency of co-citations between 2 authors A and B can be computed by finding out the commonly cited references between A and B. The frequency of co-citations between each pair of authors were found out from the cited references employing the method referenced above. In the ACA matrix, the diagonal values can either be treated as missing (Howard D. White & McCain, 1998) or be substituted by using an artificial value which is obtained by dividing the sum of the 3 highest values for a row or column by 2 as done in previous studies by Sircar et al. (2001), Culnan (1986), and H.D. White & Griffith (1981). The diagonal values were treated as missing as the results remain unaffected following either approach (McCain, 1990a).

Before proceeding with ACA for the three different periods, it was deemed appropriate only to include authors who met a fixed limit of mean co-citations in the analysis. Rules of thumb commonly employed in ACA were applied to obtain more concise and interpretable results.

Average Co-Citation Rate = Sum of Row or Column Values Except for Diagonal / N -1

Where N is the total number of authors. The filter criteria employed was that only authors with average co-citation rate equal to the number of years included in the analysis were considered. Using the filtering criteria mentioned above, 30 authors met the requirements for the period 1997-2003, 46 authors met the requirements for the period 2004-2010, and 53 authors met the requirements for the period 2011-2017.

3.1.4.2. Factor Analysis:

Factor analysis is a commonly used data reduction technique that aims to explain variability among observed and correlated variables by a lower number of unobserved variables, widely known as factors. In the context of ACA, factor analysis is performed on the author co-citation matrix, which provides the frequency with which two authors are co-cited together. Conducting factor analysis on the author co-citation matrix yields factors with the factor loadings for each author that loads on to a factor. As authors who work in functional areas tend to work with each other, borrow, and develop ideas from each other, such authors have a higher likelihood of being co-cited together and load on to the same factor. The factor loadings are indicative of the contribution of an author to a factor, with authors contributing more to a factor having higher factor loadings.

Consistent with prior ACA studies such as McCain (1990a) and Nerur et al. (2008), Principal Component Analysis (PCA) with oblimin rotation was used for generating the factors from the ACA matrix, and the minimum eigenvalue for factor extraction was kept as 1. The eigenvalue reflects the amount of variance that can be explained by a factor (Hair, Anderson, Tatham, &

Black, 1998). Furthermore, only authors with factor loadings higher than ± 0.4 were considered, to be consistent with prior ACA studies and provide more precise and interpretable factors.

As the period studied is 21 years, splitting the period into three equal durations of 7 years each can help in analyzing the changes occurring in operations management over time. The period of 1997-2017 was divided into three similar durations: 1997-2003, 2004-2010, and 2011-2017. The ACA matrices from the three different periods were subjected to PCA with oblimin rotation.

Using PCA, six factors were extracted for the period 1997-2003, seven factors were obtained for the period 2004-2010, and ten factors were extracted for the period 2011-2017. The statistical software SPSS was utilized for performing factor analysis. For the period 1997-2003, two factors were deemed uninterpretable and hence not included in the study, and for the period 2011-2017, one factor was considered to be uninterpretable and thus not included in the study. Therefore, four factors from the first period, seven factors from the second period, and nine factors from the last period were included in the analysis (Table 6).

Factor analysis, along with MDS is a powerful tool in deciphering changes in the intellectual structure of a field over a period.

Table 6. Time Periods and Factors Extracted for Each Time Period

Period	Factors
1997-2003	4
2004-2010	7
2011-2017	9

Table 7. Factors Extracted for 1997-2003 (Pattern Matrix)

Factors	Factor 1	Factor 2	Factor 3	Factor 4
Authors	*Eisenhardt* Ferdows Fine Hayes Hill Kaplan *Mintzberg* Porter Stalk *Wheelwright*	Gerwin *Gupta* *Slack* *Upton*	Clark Kaplan *Monden* Stalk Womack	*Anderson* *Boyer* *Chase* Ferdows *Garvind* Hayes *Miller* *Roth* Schonberger Swamidass *Ward*
Variance Explained	14.204	2.649	1.791	1.167
% of Variance Explained	47.347	8.829	5.970	3.889

Authors with loadings ≥ ±0.7 are displayed in Italic font.

Table 8. Factors and labels for 1997-2003

Factor	Label
1	Strategy & Dynamic Manufacturing
2	Manufacturing Flexibility & Lean
3	Production & Activity Based Costing
4	Service Operations Management

Factor analysis for the period 1997-2003 yielded four factors. Factor 1 is highly influenced by authors such as Eisenhardt whose research focus is on strategy and cognition, Mintzberg whose research topics are organization theory and business strategy theory, Wheelwright whose research interests are in the field of dynamic manufacturing and forecasting, and Stalk whose research interests are strategic management, and strategies for family business systems. Other authors such as Porter, Kaplan are loaded on to factor 1, but with comparatively lower loadings. From the dominant research themes evident from the authors that load highly on Factor 1, Factor 1 was labeled as Strategy & Dynamic Manufacturing, as this factor showcases the integration of strategic management and dynamic manufacturing in the field of operations management.

Factor 2 reflects the writings of authors such as Gupta whose research interests lie in the field of manufacturing flexibility, Slack whose research interests are in operations strategy and process management, Upton whose research interests are in manufacturing flexibility, lean, and operations based strategy, and Gerwin whose research interests are in manufacturing flexibility. Factor 2 is dominated by the research theme of manufacturing flexibility with a hint of lean and operations-based strategy. Therefore, Factor 2 was labeled as Manufacturing Flexibility & Lean.

Factor 3 is highlighted by the writings of authors such as Monden whose research interests are in the Toyota production system, Kaplan whose research interests are in the field of costing, balance card, activity-based costing, and performance management, and Womack whose research interest are in the area of lean production and lean thinking. Factor 3 was hence labeled as Production & Activity Based Costing.

Factor 4 highlights the work of authors such as Anderson known for his work in the field of customer value management, sem, measurement, Boyer whose research interests are in operations and strategy, Chase whose expertise lies in the field of service operations management, Miller whose interests are in cultural research, Roth whose research interests are in the area of manufacturing and service operations strategy and Ward whose research interests are in manufacturing strategy. Therefore, factor 4 was labeled as Service Operations Management, highlighting the interface between service and operations management. The 6-year period of 1997-2003 witnessed the use of strategic management theories as seen by citing authors such as Eisenhardt and Porter, the tremendous importance of the field of flexible manufacturing and lean manufacturing. Following the introduction of the term lean production in 1990 (Womack, Jones, & Roos, 1990) (Holweg, 2007), research in lean manufacturing has been gaining importance in the subsequent years. Finally, the field of service operations management highlights the significance of operations management in the service sector.

Table 9. Factors Extracted for 2004-2010 (Pattern Matrix)

Factors	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7
Authors	Anderson Baggozir Boyer *Chase* *Flynn* Frohlich Gerwin *Hayes* Narasimhan *Podsakoff* *Porter* *Roth* Schonberger Skinner *Swamidass* *Ward*	Aviv Cachon Chen *Cohen* Fine Fisher	Bagozzir Frolich *Handfield* Kogut *Krause* *Williamson*	Eissenhardt Gunasakeran Kaplan Slack Voss Womack Yin	Chen *Corbett* *Hopp* Lee *Vanmeighem*	Gunasakeran Hendricks Schonberger	Dyer *Federgruen* *Gallego* Graves Song Zipkin
Variance Explained	17.787	6.316	3.675	1.918	1.393	1.211	1.112
% of Variance Expl	38.666	13.731	7.990	4.170	3.029	2.633	2.418

Authors with loadings ≥ ±0.7 are displayed in Italic font.

Table 10. Factors and labels for 2004-2010

Factor	Label
1	Service Operations Management & Technological Innovation
2	Manufacturing Strategy
3	Neuroscience & Healthcare Supply Chains
4	Strategy & Cognition
5	Sustainable Operations
6	Global Supply Chain Management & Manufacturing
7	Dynamic Programming & Decision Models

Factor analysis for the period 2004-2010 yielded six factors. Factor 1 reflects the writings of authors such as Chase whose research interests are in service operations management, Flynn whose research interests are in operations strategy, Roth whose research expertise lies in manufacturing and service operations strategy, and Swamidass whose research interests are in the field of technological innovation and technology entrepreneurship. Factor 1 was hence labeled as Service Operations Management & Technological Innovation.

Factor 2 reflects the writing of authors such as Cohen, Fisher, and Fine, whose research interests lie in the field of manufacturing strategy, manufacturing capacity, and retail operations. Hence, Factor 2 was labeled as Manufacturing Strategy.

Factor 3 highlights the work of authors such as Handfield whose research interests are in the field of strategic sourcing, biopharmaceutical supply chains, healthcare supply chains, and Krause and Williamson whose research interests are in the field of supply chain operations management and transaction cost economics, and Bagozzi whose research interests ate in the field of social psychology, statistics, and neuroscience . Therefore, Factor 3 was named Neuroscience & Healthcare Supply Chains, reflecting the importance of Neuroscience & Healthcare Supply Chains in the field of operations management during the period 2004-2010.

Factor 4 reflects the writings from authors such as Eisenhardt and Kaplan, whose research expertise lies in the field of strategy and cognition. Hence, factor 4 was labeled as Strategy & Cognition.

Factor 5 is dominated by authors such as Corbett whose research interests are in the field of environmental management, entrepreneurial operations, and sustainable operations, Hopp whose research interests are in the field of supply chain management and product innovation, and Vanmeighem whose research topics are operations management and collaboration. Therefore, factor 5 was labeled as Sustainable Operations.

Factor 6 highlights the writings of authors such as Gunasekaran, Hendricks, and Schonberger, whose research interests are in the field of manufacturing and global supply chain management. Hence, Factor 6 was labeled as global supply chain management and manufacturing.

Factor 7 reflects the writings of authors such as Gallego whose research interests are in the field of revenue optimization, dynamic programming, and discrete choice models, Song whose research topics are decision models in operations and supply chain management. Hence, Factor 7 was labeled as Dynamic Programming & Decision Models.

As we move from the period 1997-2003 to the period 2004-2010, the number of significant factors extracted increases from 4 to 7, signifying the relative growth of the operations management field over those years. In the period of 2004-2010, we see the importance of operations strategy and manufacturing being carried over from the period 1997-2003. This period also saw the emergence of new topics such as neuroscience and healthcare supply chains, sustainable operations and dynamic programming and decision models. Groundbreaking research aided by vastly improved technologies such as the internet and readily available resources enabled researchers to dwell deeper into former uncharted territories to answer their research questions. In this period, the growing concerns for sustainability aided in the growth of the field known as sustainable operations. The period 2004-2010 also highlights the importance of operations research-related topics such as dynamic programming and decision models.

Table 11. Factors Extracted for 2011-2017 (Pattern Matrix)

Factors	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8	Factor 9
Authors	Anderson Bendoly *Boyer* *Ferdows* Flynn Frohlich *Hayes* Narasimhan Porter *Rosenzweige* *Schmenner* Shah *Skinner* *Swink* Womack	*Corbett* Hopp Kouvelis *Lee* *Ozer* *Sux*	Anderson Barney Choi Dyer Fornell Frohlich Hendricks Narasimhan Podsakoff Teece *Wagner* Williamson	*Neely* Teece *Voss* *Yin*	*Bental* *Chen* Kouvelis	*Guide* Pagell Porter *Zhuq*	Aviv *Cachon* Christopher Fisher Graves	Bendoly *Tversky*	*Bertsimas* Zipkin
Variance Explained	18.844	6.242	3.261	2.338	1.994	1.805	1.678	1.340	1.026
% of Variance Explained	35.555	11.778	6.154	4.411	3.762	3.405	3.166	2.529	1.935

Authors with loadings ≥ ±0.7 are displayed in Italic font.

Table 12. Factors and labels for 2011-2017

Factor	Label
1	Manufacturing & Operations Strategy
2	Supply Chain & Information Technology
3	Operations, Economy & Psychology

4	Strategy, Services, & Innovation
5	Optimization & Operations Research
6	Safety & Sustainability
7	Revenue Management & Inventory Management
8	Psychology & Behavioral Operations
9	Healthcare Analytics

Factor analysis for the period 2011-2017 yielded nine factors. Factor 1 reflects the writings of authors such as Boyer, and Ferdows whose research interests are in the field of operations, strategy, and global manufacturing. Factor 1 was hence labeled as Manufacturing & Operations Strategy.

Factor 2 highlights the writings of authors such as Lee whose research interests are in the field of supply chain management, information technology, and value chain innovations, Ozer whose research interests are in the field of supply chain management. Hence, Factor 2 was named Supply Chain & Information Technology.

Factor 3 reflects the writings of authors such as Williamson whose research interests are in transaction cost economics, Wagner whose research topics are supply chain management, logistics, purchasing and operations, Podsakoff whose research interests are in organizational behavior, industrial and organizational psychology. Hence, Factor 3 was labeled Operations, Economy & Psychology.

Factor 4 highlights the writings of authors such as Neely whose research topics are performance, strategy, services, and innovation, Teece whose research interests are in strategic management and innovation. Hence, Factor 4 was labeled as Strategy, Services, & Innovation.

Factor 5 is reflected by the writings of authors such as Bental and Chen, whose research interests are in the field of optimization and operations research. Therefore, Factor 5 was labeled as Optimization & Operations Research.

Factor 6 highlights the writings of authors such as Guide whose research interests are in the field of closed-loop supply chains, sustainable operations, remanufacturing, and industrial ecology, and Pagell whose research topics are in sustainability and worker safety. Therefore, factor 6 was named Safety & Sustainability.

Factor 7 highlights the writings of authors such as Cachon, whose research interests are in supply chain & operations management, pricing, and Aviv whose research interests are in supply chain management, revenue management, social networks, inventory management, and dynamic pricing. Therefore, Factor 7 was labeled as Revenue Management & Inventory Management.

Factor 8 is dominated by the pioneering work of cognitive and mathematical psychologist Amos Tversky. Another author loaded on to factor 8 is Bendoly, known for his work in behavioral operations, which in turn is a field which borrows heavily from economics and cognitive psychology. Hence, Factor 8 was labeled as Psychology & Behavioral Operations.

Factor 9 is dominated by authors such as Bertismas whose research topics are in the field of optimization, stochastics, analytics, healthcare, finance. Hence, Factor 9 was labeled as Healthcare Analytics.

As we move from the period 2004-2010 to the period 2011-2017, the number of significant factors extracted increases from 4 to 7, signifying the relative growth of the operations management field over those years. Throughout 2011-2017, the relevance of topics such as manufacturing and operations strategy remain intact and are carried forward from the previous years. This period saw the proliferation of economic and psychological concepts in operations management research, highlighted by Factors 3 and 8. Also, some new topics emerged, such as health care analytics, which uses analytics in the field of healthcare, to answer further research questions. The area of revenue management, inventory management, and behavioral operations management started gaining more prominence.

Apart from unraveling the growth of operations management over the past two decades, factor analysis also unveiled that some authors such as Podsakoff, Porter, and Fisher load on to factors in all three periods. This displays the importance of exerted by these authors in all three periods. Thus, functional fields such as strategic management, organizational behavior, and psychology, along with retail operations and global supply chain management are essential topics in the field of operations management throughout the 21 years analyzed.

Table 13. Factors Extracted for 1997-2017 (Pattern Matrix)

Factors	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8
Authors	Anderson *Boyer* *Ferdows* *Fine* Flynn *Hayes* *Narasimhan* *Porter* *Roth* *Schmenner* *Schonberger* *Skinner* *Slack* *Swamidass* *Ward* Womack	*Aviv* *Cachon* *Chen* *Cohen* Corbett Federgruen *Fisher* Gallego *Graves* Zipkin	Anderson *Choi* Clark Eisenhardt Fornell *Handfield* Narasimhan Podsakoff *Williamson*	Clark *Simon* Teece Voss *Yin*	Gunasekaran *Kaplan*	Corbett Gallego *Lee*	Bendoly *Dyer* Fornell Hendricks	Gunasekaran *Neely*
Variance Explained	17.272	6.680	3.827	2.315	1.444	1.185	1.099	1.089
% of Variance Expl	38.381	14.846	8.504	5.145	3.209	2.634	2.443	2.421

Authors with loadings ≥ ±0.7 are displayed in Italic font.

3.1.4.3. Multidimensional Scaling (MDS)

MDS is a data reduction technique that results in a map using similarities or dissimilarities between objects (Wilkinson, 2002). Kruskal & Wish (1978) defined proximity as “a number which indicates how similar or different two objects are, or are perceived to be, or, any measure of this kind.” Proximity matrices can be classified into similarity or dissimilarity matrices (Cox

& Cox, 2001). Proximity matrices can be used as inputs into Multidimensional Scaling software to generate proximity maps that display the relative position of authors or documents. The basic premise in using MDS on proximity matrices is that authors with closer proximity will be located closer to each other on the proximity map.

Author Co-Citation matrices are classified under similarity matrices as a higher number in the cell alludes to higher similarities between authors (Leydesdorff & Vaughan, 2006). Even though the co-citation counts in the ACA matrix can be construed as a proximity measure, the co-citation counts were converted to a more robust similarity measure between rows and columns. The most commonly used method is to compute Pearson correlation coefficients from the co-citation counts to obtain the Pearson correlation matrix, which is a similarity measure, and hence suitable for MDS in ACA (Kruskal & Wish, 1978).

For answering my second agenda of ACA, the correlations between authors are used as an input to get the MDS map of author proximities. Evolution of a field can be deciphered by studying changes in MDS maps over time.

The statistical tool SPSS was used to perform MDS. SPSS has two options for MDS: ALSCAL and PROXSCAL. ALSCAL is utilized for performing MDS on dissimilarity matrices, while PROXSCAL allows the user to stipulate whether the matrix is similarity-based or dissimilarity based. Pearson correlation matrix is a similarity measure as higher the Pearson correlation coefficient, higher the similarity between two authors. Hence, the PROXSCAL option in SPSS was utilized to perform MDS on the Pearson correlation matrix.

Only authors with factor loadings $\geq \pm 0.7$ were considered for constructing the MDS maps, for smoother and more precise interpretation. After creating maps with a different number of dimensions, it was found out that a two-dimensional solution was the best for interpretation purposes.

For unraveling the intellectual structure of operations management over the past two decades, the 21 years was split into three equal periods of 7 years each, as done in the factor analysis section. The Pearson correlation matrices from the three different periods were subjected to MDS.

Figure 6. MDS map for 1997-2003

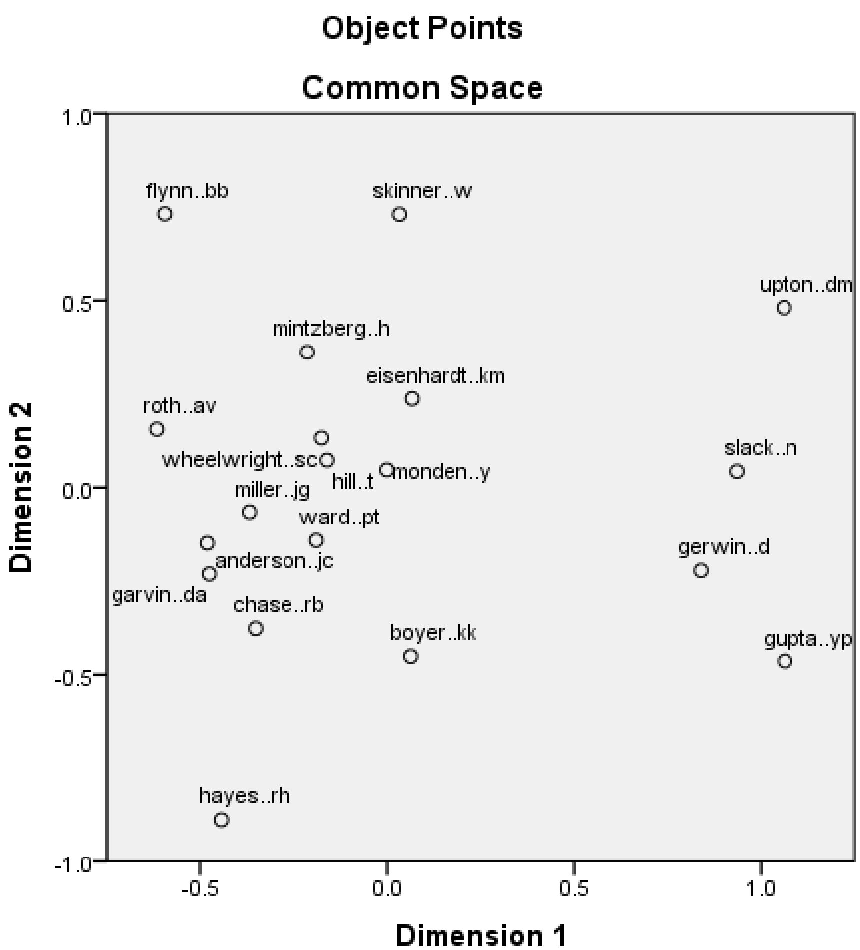


Table 14. Goodness of fit measures (1997-2003)

Normalized Raw Stress	0.03742
S-Stress	0.0886
Dispersion Accounted For (D.A.F.)	0.9625
Tucker's Coefficient of Congruence	0.9811

For the period 1997-2003, the stress measures from MDS were 0.03742 and 0.0886, which are close to 0 and the DAF and Tucker's Coefficient of Congruence were 0.9625 and 0.9811, indicating a very good fit.

For the period 1997-2003, the authors such as Eisenhardt, Ward, Chase, and Miller, who appear on the left side of the map, represent strategy and services. Authors on the right side of the map, such as Slack, Gerwin, and Upton describe the field of manufacturing flexibility. Authors such as Miller, Ward, Hill who appear close to each other on the map are cited together by other authors.

Figure 7. MDS map for 2004-2010

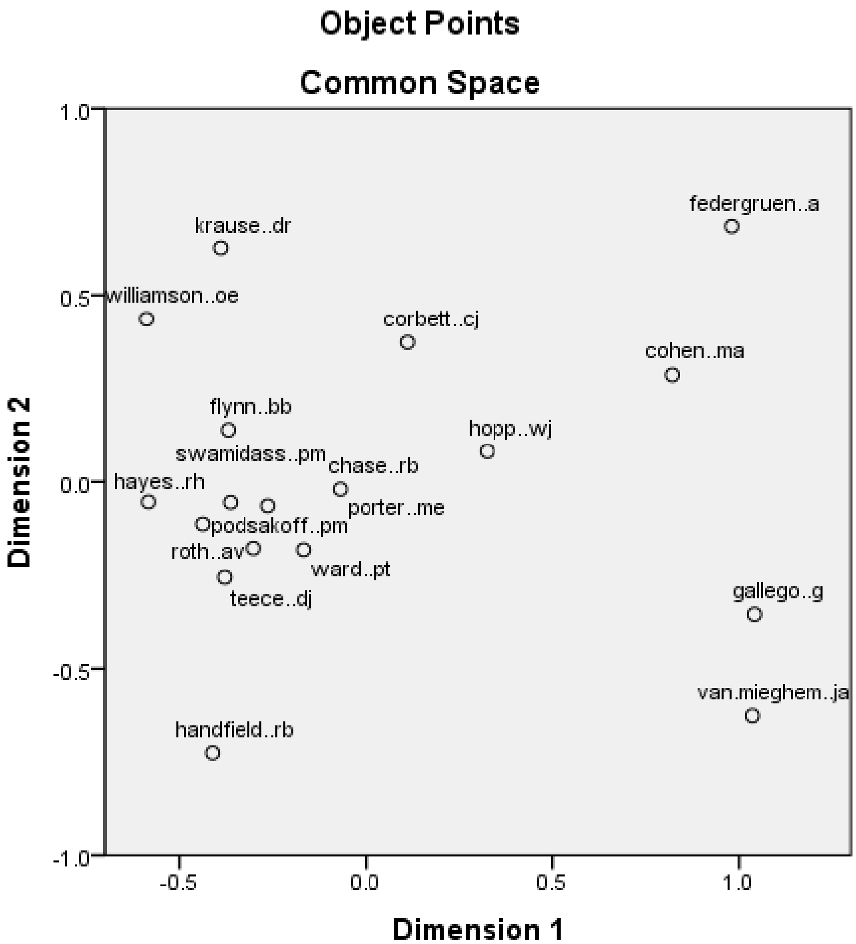


Table 15. Goodness of fit measures (2004-2010)

Normalized Raw Stress	0.03356
S-Stress	0.07727
Dispersion Accounted For (D.A.F.)	0.96644
Tucker’s Coefficient of Congruence	0.98308

For the period 2004-2010, the stress measures from MDS were 0.03356 and 0.07727, which are close to 0 and the DAF and Tucker's Coefficient of Congruence were 0.96644 and 0.98308 respectively, indicating that the fit is good.

For the period 2004-2010, the authors such as on the left side of the map represent fields such as Strategic management, and Service operations management. Authors on the right side of the map describe the field of operations research.

Figure 8. MDS map for 2011-2017

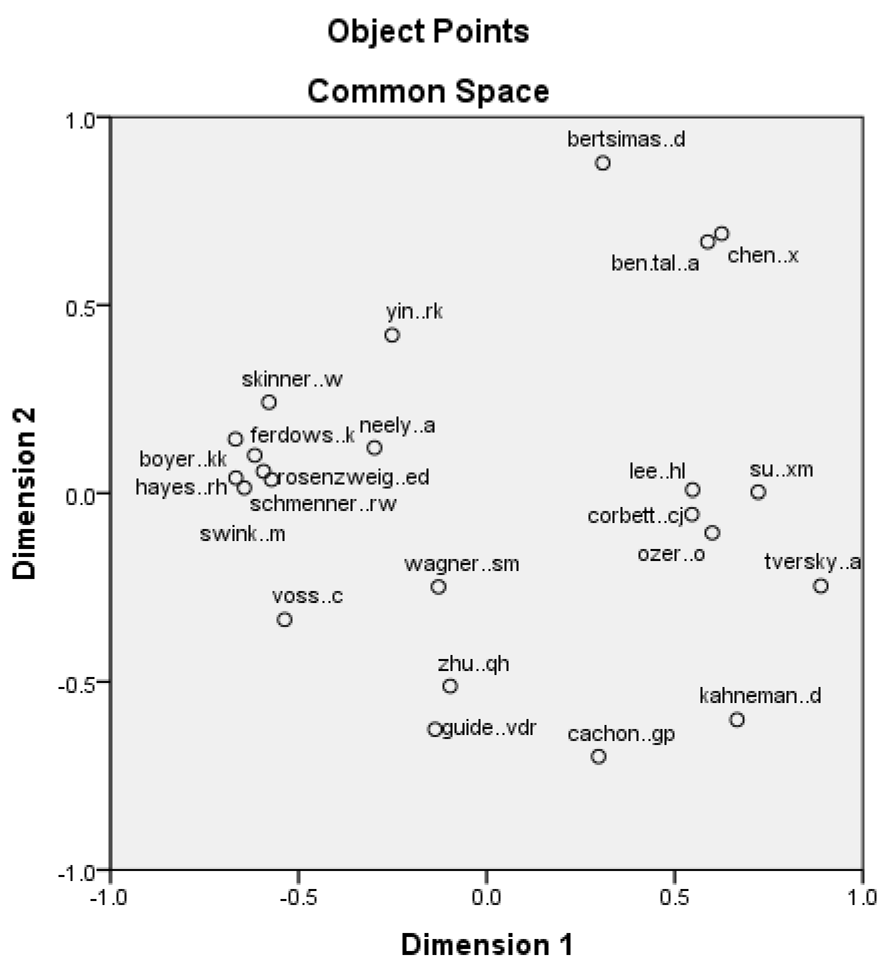


Table 16. Goodness of fit measures (2011-2017)

Normalized Raw Stress	0.04134
S-Stress	0.09796
Dispersion Accounted For (D.A.F.)	0.95866
Tucker's Coefficient of Congruence	0.97911

For the period 2011-2017, the stress measures from MDS were 0.04134 and 0.09796, which are close to 0 and the DAF and Tucker's Coefficient of Congruence were 0.95866 and 0.97911 respectively, indicating that the fit is good.

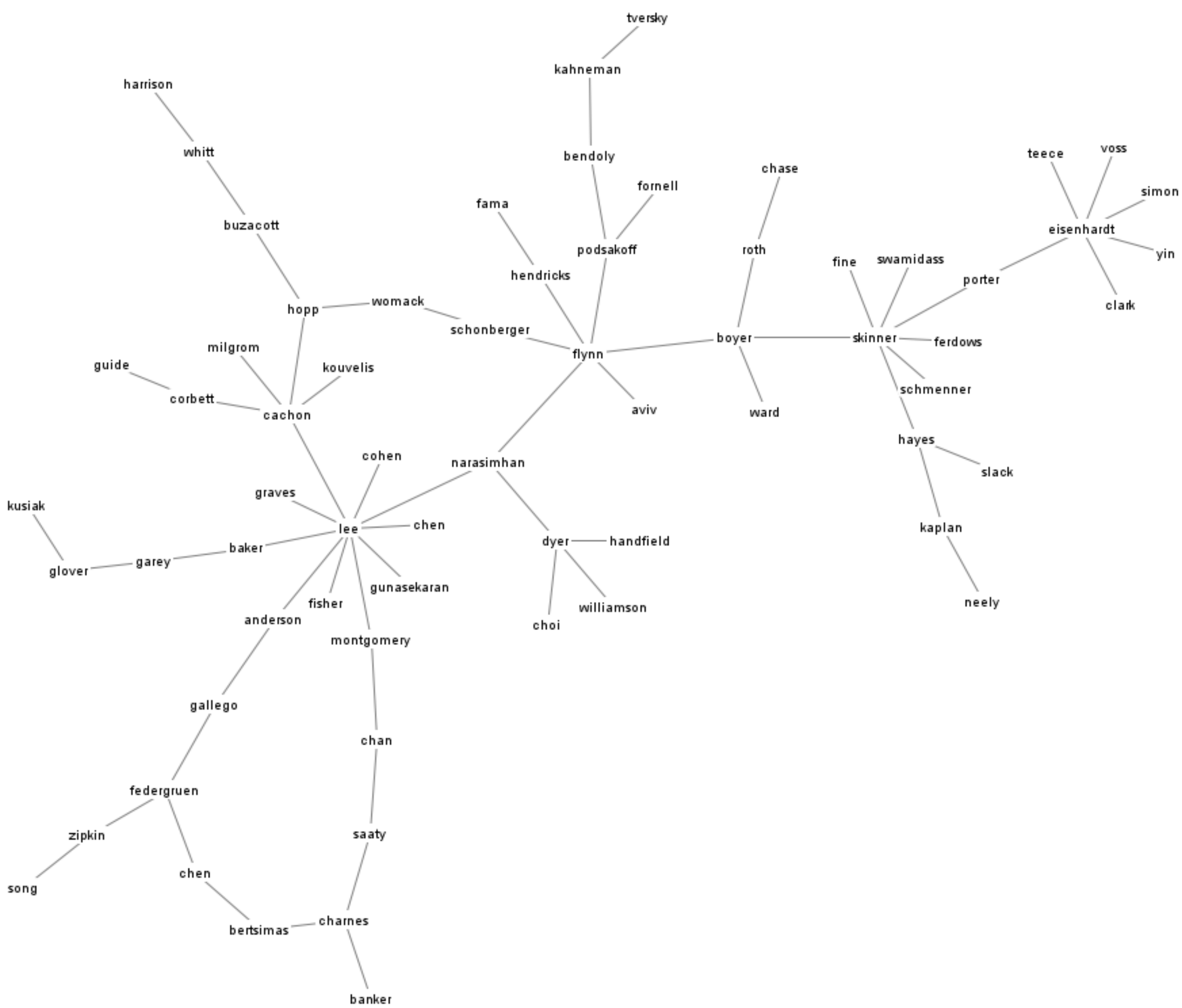
For the period 2011-2017, the authors on the left side of the map represent strategic management, while authors on the right side of the map such represent the field of economics and psychology.

Changes in the authors over the three different periods in the MDS maps show the comparative influence of various authors across those periods.

3.1.4.4. Pathfinder Network

Pathfinder analysis is commonly used in cognitive psychology, and citation/co-citation studies to showcase the central nodes of the relevant authors and to study the relationships between them (Nerur et al., 2008). Pathfinder analysis highlights the influencing direction and reciprocal relations in a network (Sullivan, Nerur, & Balijepally, 2011). The pathfinder network software JPathfinder was utilized to construct the pathfinder network. The full author co-citation matrix of the 67 selected authors was the input given into the tool, and the output was the pathfinder network diagram called the PFNet chart.

Figure 9. Pathfinder Network (Intellectual Structure of OM from 1997-2017)



From the PFNet diagram, the central nodes of the selected authors for the period 1997-2017 are Lee, Flynn, Boyer, and Eisenhardt. These authors are critical to the stability of the network of authors due to the centrality of their location in the PFNet diagram.

3.2. Term Co-Occurrence Map:

A Term Co-Occurrence Map was constructed using VOSviewer, based on text data from the title and abstract fields. The term-occurrence map specifically shows the proximities of words that can be related based on their co-occurrences. VOSviewer constructs the term co-occurrence map using the Apache OpenNLP Toolkit which identifies noun phrases and then compares their distribution of overall co-occurrence to their distribution across other noun phrases to calculate a relevance score (Van Eck and Waltman, 2011). The central insight is that noun phrases that frequently co-occur with high relevance scores are more probable in deciphering topics or themes that are underlying in the text corpus (Kapoor et al., 2017).

The minimum number of occurrences of a term in the text corpus was kept to 143, to avoid commonly used and repeated words known as stop words. Of the 177787 terms, 497 terms met the criteria. Of the 497 terms, VOSviewer selected 60% of the 497 (298) as relevant and essential. From the list of relevant terms, Man was deemed to be a stop word and hence removed.

VOSviewer identified three distinct clusters from the Term Co-Occurrence Map (Figure 9).

Figure 9. Term Co-Occurrence Map for 1997-2017

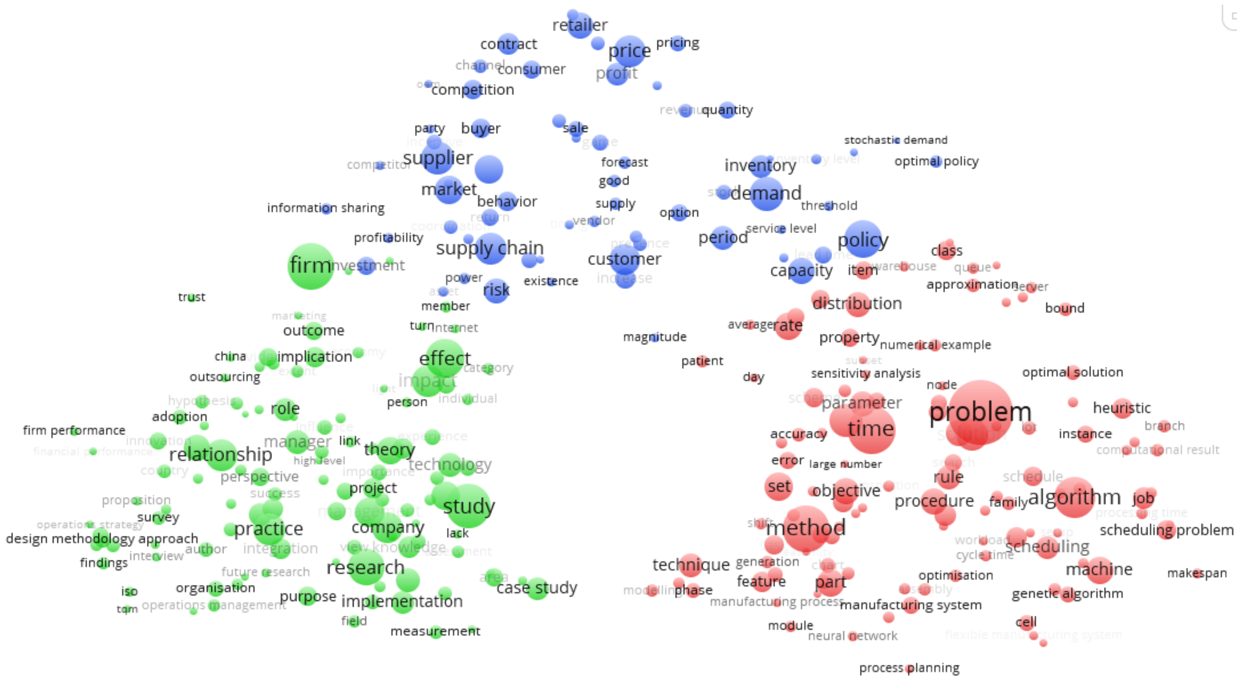
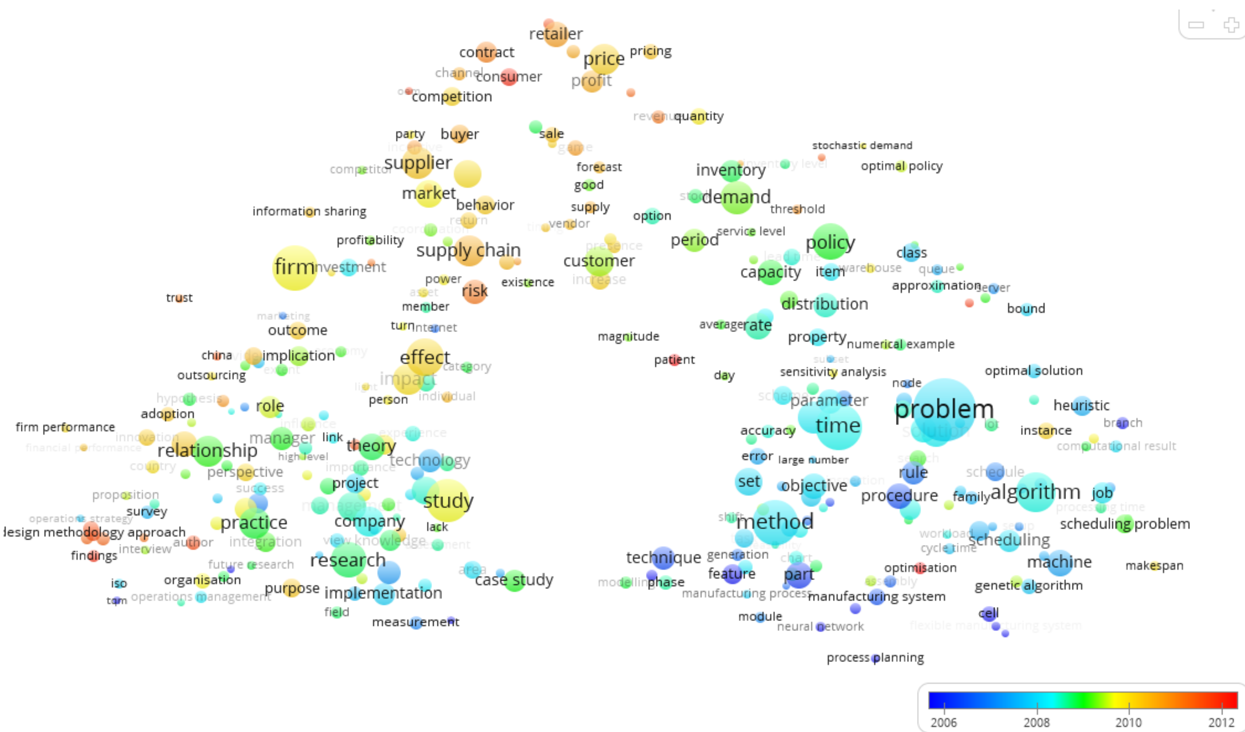


Table 17. Topic labels from Term Co-Occurrence Map

Topic	Keywords
Topic 1, Research Methodology	Research, Study, Firm, Effect, Relationship, Theory, Practise, Case Study, Role.
Topic 2, Supply Chain	Supply Chain, Customer, Supplier, Market, Retailer, Contract, Pricing, Demand, Inventory
Topic 3, Algorithm	Problem, Time, Method, Algorithm, Machine, Scheduling, Objective, Distribution, Technique

Figure 10. Term Co-Occurrence Map Overlay Visualization



The Term Co-Occurrence Map Overlay Visualization helps in identifying a change in topic trends over time. The overlay visualization indicates that in the mid-2000s, research in operations management mainly revolved around machine scheduling, algorithms, and optimization of objective functions while in recent years, research involving contracts related to the retailer, supplier, and different entities of the supply chain is gaining traction. Studies involving inventory policies and experimental studies that include paying compensation to contestants are on the rise since the year 2010.

One must note that the topics derived from the term co-occurrence map tend to be expansive in nature. Hence, textual analytic techniques were explored to better discern underlying topics from the operations management research text corpus.

Miller (2015) detailed the steps in text analytics:

- Collect the text
- Preprocess the text
- Create a term-document matrix
- Analyze text using topic modeling, sentiment analysis, etc.

Of the textual analytic techniques, topic modeling was found to be the most appropriate technique for my paper.

3.3. Topic Modeling

Topic modeling has made it easier to discern topics from a given collection of documents. Topic modeling uses statistical analysis in conjunction with algorithms to discover topics latent in a large group of documents (Blei, 2012). Topics are similar words clustered together.

3.3.1. Selecting the approach

Of the several options that are used for topic modeling such as LDA (Latent Dirichlet Allocation); Non-Negative Matrix Factorization (NNMF); Latent Semantic Analysis (LSA), LDA was selected to run topic modeling, as the results from the above-mentioned techniques are similar, and the fact that LDA is the most popular topic modeling routine.

3.3.2. Pre-processing Text:

In my research context, abstracts will be a suitable field to conduct topic modeling. The column AB from the web of science database was selected for topic modeling. Before the abstracts were subjected to topic modeling, text pre-processing steps were followed to clean the abstracts. This included pre-processing abstract texts to remove punctuation marks, transforming to lower case, removing digits, removing stop words, stripping whitespace, and stemming documents. Text pre-processing was done in programming language R (Feinerer, Hornik, & Meyer, 2008).

3.3.3. Number of Topics:

As with other topic modeling routines, the number of topics needs to be mentioned beforehand. I ran LDA with a different number of topics such as 5, 10, 15, 20, and 25. On analyzing the results with a different number of topics, the number of topics was selected to be 20, as 20 topics seemed to best represent the corpus of text provided. The number of topics below 20 did not seem to best serve the corpus and the number of topics above 20, such as 25 topics seemed to have more uninterpretable topics.

The resultant cleaned abstracts were then subjected to topic modeling in R (Grün & Hornik, 2011) to return 20 topics with the top 20 terms. In addition to the topics along with their terms, the topic assignment for each document, and the probability of each document being associated with each topic was found out.

Table 18. Topics extracted using LDA (Latent Dirichlet Allocation) for 2011-2017

Number	Terms	Topic Label
1.	optim function distribut set robust approxim general bound stochast linear class deriv	Optimisation

	show properti can valu expect problem numer probabl	
2.	relationship firm innov capabl data project manag find effect knowledg relat examin posit influenc impact collabor empir role implic right	Knowledge Capabilities
3.	inform supplier contract share mechan two buyer can game show may incent agent studi cost	Supplier Contracts

	procur effici power result one	
4.	demand cost polici inventori optim order capac alloc level period consid system lead dynam quantiti numer time show determin studi	Inventory Policies
5.	manufactur system process design develop flexibl complex resourc chang technolog plan requir environ integr support need engin present	Flexible Manufacturing

	dynam applic	
6.	decis uncertainti risk make forecast loss prefer subject result experi choic predict condit can util one theori show observ behavior	Behavioral Experiments
7.	product cost manufactur plan produc mainten compon new industri failur rate consid determin howev develop reduct prevent reduc unit reliabl	Reliability Studies

8.	firm find return market invest financi increas relat risk stock portfolio valu chang posit higher trade associ fund asset evid	Financial Portfolios
9.	problem algorithm solut propos solv comput program optimis search heurist formul constraint instanc approach generat object integ result method genet	Algorithms
10.	perform improv oper	Quality Studies

	qualiti use measur result studi factor level signific effect test indic impact show analysi plant investig practic	
11.	servic custom provid system patient time deliveri can hospit wait queue arriv delay rate use care may call reduc increas	Healthcare Operations
12.	price retail market consum profit firm	

	competit purchas sale offer increas strategi can may sell show revenu channel custom compet	
13.	suppli chain integr strategi studi respons effect manag paper coordin logist differ global sourc can provid disrupt also impact analysi	Supply Chain
14.	model new use develop paper result differ first base	Remannufacturing

	remanufactur type two exist present scenario can take demonstr structur allow	
15.	control use process data estim method variabl simul propos paramet sampl mean chart can statist base compar monitor error averag	Stattsical Porcess Control
16.	research manag practic paper studi purpos compani implement literatur develop oper environment	Sustainable Operations

	lean organis identifi adopt sustain author find implic	
17.	approach network propos use select evalu method base effici paper present appli analysi methodolog case valu applic decisionmak illustr studi	Network Studies
18.	effect find social learn individu increas experi group differ behavior influenc work user team signific	Employee behavior

	like employe particip examin worker	
19.	line assembl part machin locat use tool number system work paper propos task facil time can balanc transport storag result	Assembly line
20.	time schedul process job machin stage two due flow consid rule one setup differ shop batch sequenc order	Job scheduling

	object complet	

The topics from the operations management literature over the years 2011-2017 (Table 18) shows that there are a wide variety of topics on which research has been done.

Conclusion & Future Direction

Compared to previous studies that have done content analysis and citation analysis in the field of operations management, I have found new topics and knowledge groups in the field of operations management over the past twenty years. Author Co-Citation, along with term occurrence map and topic modeling, has identified new themes such as behavioral operations management, experimental research, finance, high technology acquisitions, etc. I also see the use of economics based, strategic management concepts, and psychology-based research gaining traction. The PFNet diagram shows the central author nodes in the field of OM over the past 21 years. My research answers the call of Pilkington & Meredith (2009) of conduct citation-based studies every 10 to 15 years to analyze intellectual changes in a particular domain.

One interesting future study can be using the probabilities of each document associated with each topic to predict which journal a paper can target using machine learning algorithms such as random forest.

As behavioral operations management, operations research and knowledge-based capabilities are gaining traction in recent years; the second and third essays are based on behavioral operations management and high technology acquisitions respectively.

As with any study, mine suffers from a few limitations. The equal treatment of citations, selection of journals, and authors can be criticized as it is a subjective decision.

Chapter 2.

Social Stress & the Newsvendor Problem

Abstract:

This paper investigates the impact of social stress on decision-making performances in a newsvendor setting. I find little support of social stressing affecting newsvendor performances, measured by expected profits of decisions. I utilize a linear adjustment model to capture learning and demand chasing behaviors. Model analysis reveals that learning moderates the negative effect of social stress on order quantity adjustment score.

Keywords: Social stress, Newsvendor problem, Behavioral operations management, Experimental study.

1. Introduction

Behavioral operations management has been gaining in prominence in the last decade (R. Croson, Schultz, Siemsen, & Yeo, 2013). The seminal paper, Schweitzer & Cachon (2000), started a trend of studying, with human subject experiments, the behaviors of individuals under the newsvendor setting. The newsvendor setting captures the fundamental thinking of the inventory problem when demand is uncertain. Ordering more than what has required leads to wastage, whereas ordering too little leads to lost sales. The optimal order quantity balances the cost of understocking with that of overstocking. Prior studies show that people systematically deviate from the optimal order quantity (Schweitzer & Cachon, 2000), and many explanations have been proposed and tested.

Most of the early newsvendor studies do not address individual differences. Recently, there has been more work in this direction. One first example is Moritz, Hill, & Donohue (2013), where individual differences were captured by the use of the Cognitive Reflection Test (CRT). The CRT score is found to be a significant predictor of individual decision-making performances in medium and high critical ratio settings. The CRT measures the propensity of an individual to engage in system one versus system 2 type of cognitive process (Frederick, 2005). Intuitively, individual differences in other aspects of psychology may also play essential roles in business decision-making.

Stress has been a focal point of research in many settings, mainly work at the office where most of the operations decisions are being made in practice. Most people have felt stress at some point in their life, and due to individual differences in stress responses, stress affects people differently (Kudielka, Hellhammer, & Wüst, 2009). The impact of stress on decision making has been studied in various contexts, but not in operations management. Perhaps, stress can improve our understanding of the observed heterogeneity between individuals in the newsvendor context. I focus on social stress induced by social interactions similar to those prevalent in the workplace. The relevance of social stress at the workplace has been highlighted by numerous researchers. Karl Albrecht (2008) described social stress as “encounter stress,” in which stress is induced by an encounter with other people. He also noted that social stress can be manifested as a result of urging of top management in many organizations on the heavy and unrelenting schedule of processing of a large number of clients by a minimum number of staff. Moreover, social stress has been described as the most common type of stressor that people experience in their daily lives (Almeida, 2013). Given the prior research done into social stress, I try to answer the question of whether social stress is beneficial or detrimental at the workplace in an operations management setting. My primary research questions are formulated as follows: (1) Does social stress impact the performance of the inventory manager? (2) Does social stress improve or deteriorate behavioral characteristics commonly exhibited in the newsvendor setting, such as learning and demand chasing?

I did not find significant evidence for a direct negative effect of social stress on performance, but in the quantity adjustment model, subjects under social stress showed improved quantity ordered when learning was above average. Also, the evidence for a decrease in the effect of demand chasing on quantity ordered under social stress was not significant in the quantity adjustment model.

Section 2 begins with the theory development behind this research. Section 3 develops different hypotheses and explains the experimental design. Section 4 describes the analysis and results. Section 5 provides a summary of the conclusion and talks about limitations in the study and avenues for future research.

2. Theory Development

2.1. Newsvendor model

In the newsvendor problem, the seller has to place an order before the demand has been realized. If he orders too high, he has leftover inventory, and if he orders too low, he has unsatisfied demand and lost sales. The decision-maker (newsvendor) has to select an order quantity Q to satisfy stochastic demand D during a single sales period. Each unit purchased has a cost c and the price earned is p for each unit sold. The cost of under-ordering (relative to demand) is C_u = p-c, whereas the cost of over-ordering (relative to demand) is C_o = c. For an order quantity Q and demand realization D, the realized mismatch cost for period is $G(D,Q)= C_o(Q-D)^+ + C_u(D-Q)^+$ and the realized profit is $\pi(D,Q) = (p-c)D-G(D,Q)$.

The expected profit is $(Q) = \int(D,)(D)dD\infty D=0$, where f(D) is the demand density function. The optimal order quantity that maximizes expected profit is $Q^* = F^{-1} (C_u / (C_u + C_o))$, where $F^{-1}(.)$ is the inverse of the cumulative distribution function for demand and $(C_u / (C_u + C_o))$ is the critical ratio. Porteus (1990) provides an excellent review of the newsvendor model and other inventory control techniques.

The seminal work by Schweitzer & Cachon (2000) on the newsvendor problem showed that individuals tend to anchor towards the mean demand. Many possible explanations have been given for the mean anchoring behavior including the random error (Su, 2008), which was tested in a paper later on (Kremer, Minner, & Van Wassenhove, 2010). Evidence for the support of learning, where subjects perform better over time was shown by Bolton & Katok (2008).

In recent years, there have been many research papers involving different variations of the newsvendor problem. Ordering behavior in a multi-item newsstand problem with resource constraints was studied, where higher budget availability aided in the profit performance for a higher profit item and service level performance for a low-profit item (Castañeda & Gonçalves, 2018). Choi & Ketzenberg (2018) studied the inverse newsvendor problem, wherein the decision to be made is the number of customers that can be served in available capacity. The optimal order quantity for the loss-averse newsvendor with back-ordering has been studied (Xu, Wang, Dang, & Ji, 2017). Strategic customer behavior in the newsvendor problem was studied by Du, Zhang, & Hua (2015), where they found evidence that strategic customer behavior leads to a lower order quantity and in turn lower price, and lower profit. There have been some papers for instance, where the newsvendor has to make many decisions, such as the one by Sayın, Karaesmen, & Özekici (2014), where the newsvendor manages his risks by investing in a portfolio of financial instruments, which are correlated to random demand and supply. Thus, decision making involves not just the optimal ordering policy, but also the optimal portfolio.

Numerous researchers have called for incorporating individual biases for decision-makers in inventory management problems, including Bendoly, Donohue, & Schultz (2006), and Rachel Croson & Donohue (2006). Following this, in recent years, research incorporating individual biases of decision-makers in the newsvendor problem has been gaining traction. One of the first paper to include personal preferences was by Moritz et al., (2013) that tested the impact of cognitive reflection on decision-making in the newsvendor problem. Moritz et al. (2013) found that cognitive refection was a significant predictor of decision-making in the medium and high critical ratio conditions, but not in the low critical ratio conditions.

A study on gender differences in newsvendor decision making found evidence for males ordering higher in a high-profit condition (De Véricourt, Jain, Bearden, & Filipowicz, 2013). The authors base this decision making on gender differences in risk-taking.

2.2. Stress and Social Stress

Stress, in the physiological context, can be explained as a relationship between external conditions and the current state of the person, and the literature shows that stress often arises when demands on an individual exceed their resources (Burke, 1991).

Two theoretical points of view that can be used in stress are overload and interruption (Mandler, 1982). Overload results when a person’s abilities cannot keep up with external demands (House, 1974). “When one’s comfort zone of human contact has been exceeded, he begins to feel the physical stress reaction as a manifestation of the need for aloneness” (Karl Albrecht, 2008). Interruption theory is based on the premise that interruption occurs whenever an organized action or thought process is interrupted (Burke, 1991). Social stress is the stress that arises from relationships, social interactions, and the social surroundings in general. Social stress can be defined as "the feelings of discomfort or anxiety that individuals may experience in social situations, and the associated tendency to avoid potentially stressful social situations" (Wadman, Durkin, & Conti-Ramsden, 2011). The three main categories of social stressors are life events that are abrupt changes which require the quick adaptation by an individual such as a sudden injury, chronic strains which are persistent events which require adjustments from an individual over an extended period of time such as unemployment, and daily hassles which are minor events that require adaptation throughout the day such as disagreements (Karr, Deborah, 2013).

Social stress can be well understood using the interruption theory. Interruption results either when an expectation is disconfirmed, or an initiated activity is not completed. The anxiety caused by the interruption (stress) can serve as a signaling system which can result in the adaptive response to significant events or draw attention away from other needed areas (Baddely, 1972). A study done by Kirmeyer (1988) has shown the process of interruption, where she studied police radio dispatchers whose completion of specific tasks on the job were frequently disrupted as a result of new calls coming in. She was able to show that the amount of anxiety that dispatchers experience is directly related to the number of external disruptions that occur per hour. Berscheid (1983) has pointed to several studies using emotion to show the process of interruption such as one study which alluded that in romantic love, interruptive obstacles seemed to act to boost passion rather than decrease it.

Burke (1991) linked identity theory with interruption theory to better explain social stress. An identity process can be thought of as a feedback loop that is continuously operating and self-adjusting. Individuals have to adjust behavior continually to keep their reflected assessments compatible with their identity standards or references. Often in familiar situations, this adjustment process is nearly automatic. As the identity process is continuous, the difference between one's reflected assessment and identity reference is kept small. A relatively large discrepancy tends to indicate some form of interruption in the identity process that has disrupted the reasonable condition of continuous compatibility between one's reflected assessments and identity standard (Burke, 1991).

2.2. Stress and decision-making

The body responds to stress by sympathetic nervous system activation, resulting in the fight-or-flight response (Cannon, 1913). Concerning the neurobiological correlates of decision making, decision making involves a complex neural network. There is an intricate connection between stress and decision making, on the behavioral level and neural level (Starcke & Brand, 2012). Despite the heterogeneous models of stress, there is a consensus among researchers that stress elicits psychological, physiological and behavioral reactions and there is a huge difference in stress reactions among individuals (Starcke & Brand, 2012).

In my paper, I focus on the relationship between decision-making and social stress. Prior research on stress has shown that stress-induced by social stress tests alters decision-making. Laboratory stressors can be used to simulate the natural stressors that elicit stress reactions (Starcke & Brand, 2012). The majority of the laboratory stressors comprise of a physical challenge (heat, cold, pain), a cognitive demand (mental arithmetic, analytical tasks) and a social-evaluative threat like anticipation or actual performance of a public speech. Stressors are timed differently to the task of interest (decision-making) to investigate the effect of stress on the decision-making task. The stress test is conducted before the job of interest to secure maximum stress reaction during the task (Starcke & Brand, 2012).

One of the standard stress-inducing test that merges a social-evaluative threat and a cognitive demand is the TSST, abbreviated as Trier Social Stress Test (Kirschbaum, Pirke, & Hellhammer, 1993). To study the effect of stress on decision-making, stress induction has to be successful. The relation between social stress and strategic decision-making was shown in a study where participants play a beauty contest game after being randomly assigned to TSST-G or placebo version of TSST-G. Participants in the stress condition chose higher numbers in the beauty contest game than participants in the non-stress condition, indicating less strategizing (Leder, Häusser, & Mojzisch, 2013). The effect of social evaluative threat on anchoring and adjustment was shown in a study, where participants were subjected to a modified version of TSST, where stress was shown either as a threat by providing negative feedback or a challenge by giving positive feedback (Kassam et al., 2009). The participants subjected to the threat condition adjusted less than participants subjected to the challenge condition. This was explained by the fact that adjustment from self-generated anchors depends on the mental effort expenditure and adjustments can be insufficient when cognitive resources are diminished (Kassam et al., 2009). Individual factors such as age, gender, personality variables, and demographics can moderate the effect of stress on decision-making (Starcke & Brand, 2012).

Some of the previous research has focused on positive social interactions, such as the study by Heinrichs, Baumgartner, Kirschbaum, & Ehlert (2003), wherein a group of subjects before the TSST was provided social support in the form of a friend providing support in preparation of the task, a group of subjects received intranasal oxytocin, and a group of subjects received neither social support nor oxytocin. The group that received social support and oxytocin had the lowest levels of cortisol along with increased calmness and reduced anxiety, whereas the subjects that received no social support or oxytocin exhibited reduced patience and increased anxiety.

2.3. Stress in the business workplace

The workplace has gone through a tremendous evolution over the past few decades. Forty to fifty years back, work used to be more systematic and organized with individual work being the norm. In the past twenty years or so, business forces and technological advances together have entirely changed the structure of the workplace (Judith Heerwagen, J.H. Heerwagen, Kevin Kelly, 2006). The key factors that contributed to the changing nature of work can be considered to be companies' quest to be more agile and customer-oriented to counter increased competition, and massive breakthroughs in information technology that provide excellent access to information and help in separating work from time and space (Judith Heerwagen, J.H. Heerwagen, Kevin Kelly, 2006). Due to different competitive forces in play, the workplace has turned more cognitively complicated, more team-based and collaborative, more time-pressured, and more dependent on social skills. As companies become agiler, this has changed the workplace by requiring the workers to be more cognitively and socially competitive. Cognitive competence requires workers to be well versed in different tasks and levels of complexity as well as be updated in new technologies, whereas social and interactive capability requires the worker to be good team players, i.e., having good teamwork and negotiation skills (Judith Heerwagen, J.H. Heerwagen, Kevin Kelly, 2006). The changing workplace and companies' desire to be more sharp point to the worker being more involved in teamwork and social interactions. To a certain extent, we can say that social and interactive competencies have become a core essential for the current generation of workers. These social interactions and ever increased burden to do a lot of work in very little time can generate lots of unwanted stress on the worker. In order to achieve better output in the changing workplace, companies have been promoting open office spaces. Open office spaces have been gaining prominence since the 1970s (Brennan, Chugh, & Kline, 2002). Open office spaces differ from traditional office spaces in that they do not have private areas for workers. The layout is flexible and is done in such a way as to improve collaboration and remove communication barriers. In the United States of America, around 70% of offices have implemented this design with the hope of boosting morale, productivity, lowering costs, and thus improving the bottom line. Prior research on open office environment points towards an increase in noise and distractions as opposed to a traditional office environment (Hedge, 1982). Taking the organizational behavior characteristics of workers into consideration, open offices are related to an increase in physical stress, a decrease in job satisfaction, and team member relations (Brennan et al., 2002). A few studies (Allen & Gerstberger, 1973) (Zahn, 1991) point to positive outcomes from implementing open office spaces such as improved communication among workers and better judgment. For the most part, though, the literature on open office spaces show predominantly adverse effects of implementing open office spaces (Brennan et al., 2002). One of the lab studies involving open offices showed that irrelevant speech resulted in mental workload, poor performance, stress, and fatigue (Smith-Jackson & Klein, 2009).

In the book Stress and the Manager: Making it work for you, Karl Albrecht (2008) discussed encounter stress, which is stress commonly occurring in the workplace. Encounter stress can be explained as the stress caused by interactions with people, where people can get overwhelmed or drained.

Our paper deals with social stress, which is closely associated to encounter stress. Karl Albrecht (2008) emphasizes that social stress is every day in the business environment. Social stress is common both in the micro and macro environment and is considered to be the most frequent type of stressor that people encounter in their daily lives and affects people more fiercely than other kinds of stressors (Almeida, 2013).

The motivation for our research stems from the fact that there might be situations in which the inventory manager has to make an order quantity decision under a stressed environment. A typical example for inventory ordering under a stressful environment can be ordering inventory for fast-fashion retailers such as H&M and Zara, as fashion styles change rapidly, and companies have to keep up to accommodate this fast-paced changes in trends. Fast-fashion retailers can be classified under the single-period inventory model as these retailers place large orders for a single season and sell the unsold goods at clearance prices and have a very close resemblance with the newsvendor model (Cachon & Swinney, 2011). An inventory manager, apart from making newsvendor decisions, can be involved in making other decisions or maybe making simultaneous newsvendor decisions (Chen & Li, 2016). In the current work environment, these inventory managers might be working in an open office environment or in an environment that is highly conducive to social interactions, thereby causing social stress.

2.4. Measuring Stress

The Stress Overload Scale (Amirkhan, 2012) was used to measure stress reactions (Appendix A). Items related to the factor event load were used in my study as I focus on social stress. Event load has been described as the perceived burdening from outside demands, responsibilities, and pressures (Amirkhan, 2012). The Stress Overload Scale is considered to be highly reliable, valid, and efficient (Amirkhan, Urizar, & Clark, 2015).

3. Hypotheses and Experimental Design

3.1. Hypotheses

Social stress has been shown to add extra cognitive load, and people have been shown to exhibit less strategizing, which affects their performance. The first hypothesis deals with the effect of social stress on average expected profit in the newsvendor problem.

The diminished cognitive demands caused by social stress can cause the subject to use more uncomplicated strategies for decision making, which may be less effective than the trained approach. Therefore, the first hypothesis was developed as follows:

H1. (Social stress and performance). When executing repeated newsvendor decisions, subjects under social stress exhibit worse performance compared to the subjects in the baseline.

Short bursts of the stress hormone cortisol can lead to boosting the brain's openness to learning (Jain, 2015). I argue that short bursts of the stress hormone cortisol, can lead to learning which in turn can moderate the negative effect of social stress on order quantity adjustment score, where order quantity adjustment score is the difference between the current order quantity and the previous period order quantity. The second hypothesis deals with the interaction effect of learning and social stress on order quantity adjustments made by subjects undertaking the newsvendor problem.

H2. (Social stress, Learning, and Order Quantity Adjustment Score). When executing repeated newsvendor decisions, learning moderates the negative effect of social stress on order quantity adjustment score.

As subjects under social stress tend to make adjustments that are insufficient (Kassam et al., 2009), I argue that that social stress can moderate the positive effect of chasing on order quantity adjustment score.

H3. (Social stress, Chasing, and Order Quantity Adjustment Score). When executing repeated newsvendor decisions, social stress moderates the positive effect of chasing on order quantity adjustment score.

As subjects with higher CRT (Cognitive Reflection Test) scores get higher profits on average, have lower standard deviations and a lower tendency to demand chase due to the subjects with higher CRT score moderating their initial “gut” response (system one response) with intellectual thinking, I argue that CRT will moderate the negative effect of learning on order quantity adjustment score.

H4. (CRT, Learning, and Order Quantity Adjustment Score). When executing repeated newsvendor decisions, CRT moderates the negative effect of learning on order quantity adjustment score.

As subjects have both system 1 response from the brain, and the system 2 response which includes intellectual thinking and moderates the system 1 response, I hypothesize that subjects with higher CRT scores, i.e. more system 2 response will demand chase less in comparison with lower CRT scores (Moritz et al., 2013), and that CRT will moderate the positive effect of chasing on order quantity adjustment score.

H5. (CRT, Chasing, and Order Quantity Adjustment Score). When executing repeated newsvendor decisions, CRT moderates the positive effect of chasing on order quantity adjustment score.

3.2. Experimental Design

The experiments were performed on human subjects. The newsvendor problem was used as it is the cornerstone of behavioral operations management problems. The programming and implementation of the experiment were done using the software z-Tree (Fischbacher, 2007). The two experimental treatments were baseline and social stress. Undergrad students from a major public university in the United States of America were used as subjects, following standard economic experiments and the fact that previous studies have shown that the decision-making of managers does not deviate significantly from that of undergrads in a controlled lab setting

(Bolton, Ockenfels, & Thonemann, 2012). A total of thirty-four students participated in the experiments.

Baseline: Baseline refers to the control group, the standard newsvendor problem with the high-profit condition, i.e., uniform demand distribution of 1-300, price of $12 and cost of $3 (Schweitzer & Cachon, 2000), following the standard setting used in prior studies (Wu & Chen, 2014). Before the start of the experiment, students completed the CRT (Cognitive Reflection Test, Appendix B). In the newsvendor game, there were 105 rounds in total, which comprised of 5 trial rounds and 100 paying rounds. For each round, time limit to enter the order quantity was kept to 30 seconds, but not enforced. After each round, subjects were shown a review page, which showed the previous round order quantity, price, cost, profit, and cumulative profit for 15 seconds. Twenty-two undergrad students participated with an average payment of $15. After completion of the newsvendor game, students completed the Stress Overload questionnaire.

Social stress: Before the students participated in the newsvendor game, students in this group were subjected to a simplified version of the Trier social stress test (Kirschbaum et al., 1993) to induce social stress. The simplified Trier social stress test was used, as it was found to be ideal for implementing a business lab experiment.

It is imperative to distinguish social stress from environmental stress (Burke, 1991). Environmental stress is the negative psychological response of a subject to an environmental stimulus (Gatersleben, Birgitta, 2016) such as noise, pollution, carcinogens, etc. Research on the effect of environmental stress on humans has been well studied both in the laboratory and field.

My experiment has been designed to induce only social stress. I am not looking into stress caused by noise or communication in the office environment.

Simplified Trier Social Stress Test: Each student was primed to induce social stress by participating in an interview before the newsvendor game. The participant was welcomed to the lab, and informed consent was obtained. After this, the participant was taken to the interview room, where there are two confederates. The Confederates are the interviewers. The Confederates acknowledged the arrival of the subject with a brief nod of their head. The Confederates remained expressionless during the encounter and maintained eye contact with the subject throughout. Each Confederate had a notepad on a clipboard in front of them for taking notes during the interview. The following script was read by one of the Confederates to the subject following Birkett (2011): "This is the speech preparation portion of the task; you are to mentally prepare a five-minute speech describing why you would be a good candidate for your ideal job. Your speech will be videotaped and reviewed by a panel of judges trained in public speaking. You have ten minutes to prepare and your time begins now". After ten minutes, the Confederates returned to the interview wearing lab coats. The following script was read to the participant: "This is the speech portion of the task. You are to deliver a speech describing why you would be a good candidate for your ideal job. You should speak for the entire five-minute time period. Your time begins now." The prop video camera was turned on at that moment to increase evaluative/performance stress. If the participant stopped talking during the speech, he or she was allowed to remain silent for 20 seconds. If he or she did not resume speaking, the participant was prompted to continue speaking by saying: "You still have time remaining." If the subject asked the Confederates a question, Confederate1 made neutral comments, such as "Do whatever you think is best," "Say whatever comes to your mind," or "Be as creative as you like." When the five-minute alarm sounded, Confederate1 said: "Please stop, your time is up." The subjects were videotaped during the interview to induce stress, as it is known that people tend to feel anxious or distressed when they know that are under evaluation or are about to be evaluated (Kenneth A. Holroyd, 1982). Also, the design of the TSST is such that there are interruptions that aim to break the identity process of the subject, and the subject has to make continuous adjustments. After the interview, the subject was taken back to the lab, where they completed the newsvendor experiment as outlined in the baseline treatment. This was followed by the students completing the Stress Overload questionnaire. Participants in the social stress group had significantly higher negative affect scores compared to the participants in the baseline. Twelve undergrad students participated with an average payment of $15.

4. Analysis and Results:

4.1. Summary observations

Table 1. Descriptive Statistics (Order Quantity, Order Quantity Root Mean Square Error and Average Expected Profit).

Treatment	N	Min Avg exp profit	Max Avg exp profit	Mean Avg exp profit	Std-dev Avg exp profit	Min RMSE	Max RMSE	Avg RMSE	Std-dev RMSE	Min Avg Order Q	Max Avg Order Q	Mean Avg Order Q	Std-dev Avg Order Q
Baseline	22	575.72	989.54	837.84	87.20	33.94	189.58	101.88	37.54	141.54	212.54	162.11	16.31
Social Stress	12	680.12	903.70	826.68	63.67	73.75	145.69	101.45	21.08	108.20	174.87	148.97	21.24

Thirty-four undergrad students participated in the study, of which eighteen were male and sixteen females. All descriptive statistics such as mean average expected profit, mean RMSE, and mean average order quantity are shown in table 1.

4.2. Regression on Event Load Scores

A multiple linear regression model was run to check if the social stress induction was successful or not. This model tested if the event load score was significantly higher for subjects under social stress in comparison to the reference group baseline.

The event load scores were significantly higher for subjects under social stress in comparison to the baseline (Table 2). This led to the conclusion that the treatment, i.e., social stress induction, was successful.

Table 2. Manipulation Check, Regression on Event Load Scores (Social Stress vs. baseline):

Event Load	Coef.	Std. Err.	t	P>|t|
(Intercept)	17.136	1.862	9.204	1.66e-10***
Social stress	12.697	3.134	4.052	0.0003***

4.3. Regression and random-effects model

Subject's performance on the newsvendor game was tested using multiple linear regressions with average expected profit as the dependent variable. The first regression was run to test the effect of social stress (dummy variable with 0 as baseline and 1 as Social Stress) on average expected profit. CRT and gender were added to the regression model as control variables. The second regression uses event load scores as an independent variable instead of the dummy variable social stress, as event load is a more direct measure of the stress. The programming language R was used to run both regression models.

Table 3. Regression on Average expected profit (H_1: Social Stress vs. baseline):

Average exp profit	Coef.	Std. Err.	t	P>|t|
(Intercept)	866.184	32.876	26.347	<2e-16***
Social Stress	-21.726	28.873	-0.752	0.458
CRT	-0.862	12.856	-0.067	0.947
Gender	-49.874	30.410	-1.640	0.111

Table 4. Regression on Average expected profit using Event load scores (H_1):

Average exp profit	Coef.	Std. Err.	t	P>|t|
(Intercept)	902.662	54.005	16.714	<2e-16 ***
Event load	-1.525	1.457	-1.047	0.3034
CRT	-6.317	14.053	-0.449	0.6563
Gender	-58.276	32.090	-1.816	0.0794*

There was not sufficient evidence to support the first hypothesis that social stress reduces performance at the 0.05 significance level although coefficients are in the hypothesized direction (Tables 3-4), i.e. the observed negative treatment-related effect and event load related effect could likely have occurred by chance.

For learning the behavior of participants, a learning adjustment model was used. This model is a time lag linear partial adjustment model that incorporates learning and demand chasing behaviors shown in previous papers (Bostian, Holt, & Smith, 2008).

$Q_t = Q_{t-1} + \beta_0 + \beta_1 (Q^*-Q_{t-1}) + \epsilon_t$ (learning model)

Here, β_1 is the learning adjustment rate between 0 and 1. If $\beta_1 = 0$, there is no learning adjustment. If β_1 is 1, Q_t adjusts toward optimal quantity Q*. After adding in demand chasing, the model becomes:

$Q_t - Q_{t-1} = \beta_0 + \beta_1 (Q^*-Q_{t-1}) + \beta_2 (D_{t-1}-Q_{t-1}) + \epsilon_t$

β_2 represents the degree of demand chasing, i.e., moving towards the past realized demand relative to their last order quantity. $\beta_2 = 1$ represents perfect demand chasing. Social Stress, CRT, Gender, and interaction terms were added to the model above to get the following model:

$Q_t - Q_{t-1} = \beta_0 + \beta_1 (Q^*-Q_{t-1}) + \beta_2 (D_{t-1}-Q_{t-1}) + \beta_3$ (Social Stress) $+ \beta_4$ (CRT) $+ \beta_5$ (Gender) $+ \beta_6$ (Social Stress*learn) $+ \beta_7$ (Social Stress*chase) $+ \beta_8$ (CRT*learn) $+ \beta_9$ (CRT*chase) $+ \beta_{10}$ (Gender*learn) $+ \epsilon_t$

As there are 100 rounds and different individuals, a panel data was formed. This panel data was used to run a random-effects model with the adjustment score $Q_t - Q_{t-1}$ as the dependent variable. Individual heterogeneity of people has been shown in the field of cognitive psychology (Stanovich & West, 2000) and applied in the field of operations management with respect to worker performance in assembly lines (Doerr, Mitchell, Freed, Schriesheim, & Zhou, 2004), inventory decision making in newsvendor problem (Bolton & Katok, 2008) (Wu & Chen, 2014) (Moritz et al., 2013). I assume people to be heterogeneous. The random-effects model was deemed appropriate for my study, as it can help in controlling for unobserved heterogeneity when the heterogeneity is constant over time and correlated with independent variables. One hundred rounds were used in our experiment to study the learning effect (Bolton & Katok, 2008).

The programming language R was used to run the random-effects model (Croissant & Millo, 2008), with the baseline experiment taken as the reference group.

Table 5. Mean and Standard deviations of Learn, Chase, CRT, Eventload, Gender.

	mean	std dev	mean+sd	mean-sd
learn	67.76203	62.40159	130.1636	5.36044
chase	-4.79352	99.7818	94.98828	-104.575
CRT	1.323529	1.173459	2.496988	0.15007
Eventload	21.61765	10.57732	32.19497	11.04033
Gender	0.470588235	0.50664	0.977229	-0.03605

Table 6. Social Stress Random Effects Model (Capturing behavioral characteristics such as learning, chasing).

Balanced Panel: n=34, T=99, N=3366

Effects	Variance	Standard Deviation	Share
Idiosyncratic	2471.48	49.71	1.009
Individual	-21.08	NA	-0.009
Theta: -1.537			

adj	Coef.	Std. Err.	t	P>|t|
(Intercept)	7.243	2.700	2.681	0.007
Learn	-0.093	0.034	-2.686	0.007

Chase	0.291	0.020	14.209	< 2.2e-16
Social stress	-14.539	2.736	-5.313	1.147e-07
CRT	-3.507	1.170	-2.996	0.002
Gender	-10.134	2.016	-5.026	5.258e-07
Social stress*Learn	0.120	0.035	3.413	0.0006
Social stress*Chase	-0.004	0.025	-0.192	0.423 (1-tailed)
CRT*Learn	0.090	0.015	5.673	1.519e-08
CRT*Chase	-0.054	0.010	-5.141	2.876e-07
Gender*Learn	0.117	0.026	4.390	1.164e-05

Adj is the adjustment score, i.e., the difference between the current order quantity and the previous period order quantity. From table 6, we see that there is significant negative learning as the variable learn had a significant adverse effect on the adjustment score, and social stress had a significant adverse impact on the adjustment score. The interaction effect of social stress and learning was highly significant in the positive direction, i.e., learning moderated the negative impact of social stress on order quantity adjustment score. Chasing had a highly significant positive impact on order quantity adjustment score. However, since the interaction of social stress and chase was not significant, there was insufficient evidence to support the third hypothesis.

The variable CRT had a significant adverse effect on order quantity adjustment score. The interaction effect of CRT and learning was highly significant, i.e., CRT moderated the negative effect of learning on order quantity adjustment score, providing sufficient evidence to support the fourth hypothesis. Since chasing had a highly significant positive impact on order quantity adjustment score, and the interaction of CRT and chasing was highly significant and negative, CRT moderated the positive impact of chasing on order quantity adjustment score, supporting the fifth hypothesis.

A second random-effects model was run using the adjustment score as the dependent variable and the event load score as a measure of social stress, along with the rest of the independent variables from the first random effects model (Table 7).

Table 7. Event Load Random Effects Model (Capturing behavioral characteristics such as learning, chasing).

Balanced Panel: n=34, T=99, N=3366

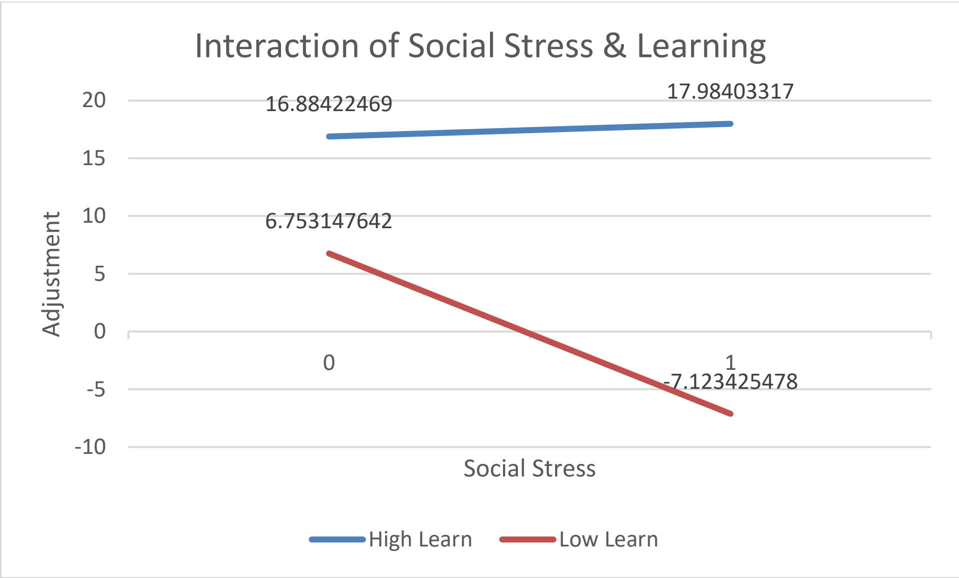
Effects	Variance	Standard Deviation	Share
Idiosyncratic	2465.57	49.65	1.008
Individual	-20.20	NA	-0.008
Theta:	-1.302		

adj	Coef.	Std. Err.	t	P>|t|
(Intercept)	17.093	4.407	3.877	0.0001***
Learn	-0.212	0.055	-3.7975	0.0001***
Chase	0.362	0.035	10.277	< 2.2e-16***
Event load	-0.688	0.130	-5.294	1.271e-07***

CRT	-4.018	1.259	-3.191	0.001***
Gender	-11.124	2.221	-5.007	5.790e-07***
Event load*Learn	0.007	0.001	4.585	4.694e-06***
Event load*Chase	-0.002	0.001	-2.352	0.018**
CRT*Learn	0.097	0.017	5.735	1.056e-08***
CRT*Chase	-0.061	0.010	-5.688	1.396e-08***
Gender*Learn	0.133	0.028	4.598	4.420e-06***

From tables 6 and 7, we see that there is highly significant interaction between learning and social stress. This result was in conformance with the second hypothesis. This can be due to short bursts of the stress hormone cortisol generated while playing the newsvendor game, which improved the brains openness to learning (Jain, 2015). It can also be explained by the possibility that the students perceived the newsvendor game as a challenge rather than a threat (Starcke & Brand, 2012). Therefore, there is sufficient evidence to support the second hypothesis.

Figure 1. Interaction Plot of Learning & Social Stress on Order Quantity Adjustment Score (H_2):



In the interaction plot (Figure 1), the Y-axis represents the order quantity adjustment score, and the X-axis represents the baseline group (0) or the social stress treatment group (1). The effect of social stress on order quantity adjustment depends on the level of learning, i.e., either high (mean learning+1sd) or low (mean learning-1sd). At a lower level of learning, social stress has a negative effect on order quantity adjustment score. However, at a higher level of learning, social stress has a slight positive effect on order quantity adjustment score.

5. Discussion and Conclusion

In this paper, I have studied the impact of social stress on individual performances in a newsvendor setting. I induce social stress by having the decision-maker participate in the Trier Social Stress Test before the newsvendor task. I find that social stress did not have a noticeable impact on performance. However, I find that learning moderates the negative effect of social stress on order quantity adjustment score, and that CRT moderates the negative effect of social stress on order quantity adjustment score, and the positive effect of chasing on order quantity adjustment score.

There are several natural extensions of this research. Since stress has a physiological component, one direction is to combine behavioral decision-making experiments with neuroscience. New studies can use more advanced technologies such as the Montreal Imaging Stress Task, a study in which acute stress induction is combined with functional imaging. Another direction is to explore different situations and variations of social stress. One such exciting variety is social stress with social support, which embodies positive social interactions, and can be induced in a lab setting by having one group bring in their best friend to provide instrumental and emotional support during the preparation phase of the social stress experiment (Heinrichs et al., 2003). A third direction is to integrate the study of stress into business environments with strategic interactions. For example, it is easy to extend a newsvendor setting to a supply chain contract setting by adding an upstream supplier.

Chapter 3.

Mergers & Acquisitions: Knowledge Relatedness and Cosine Similarity

Abstract

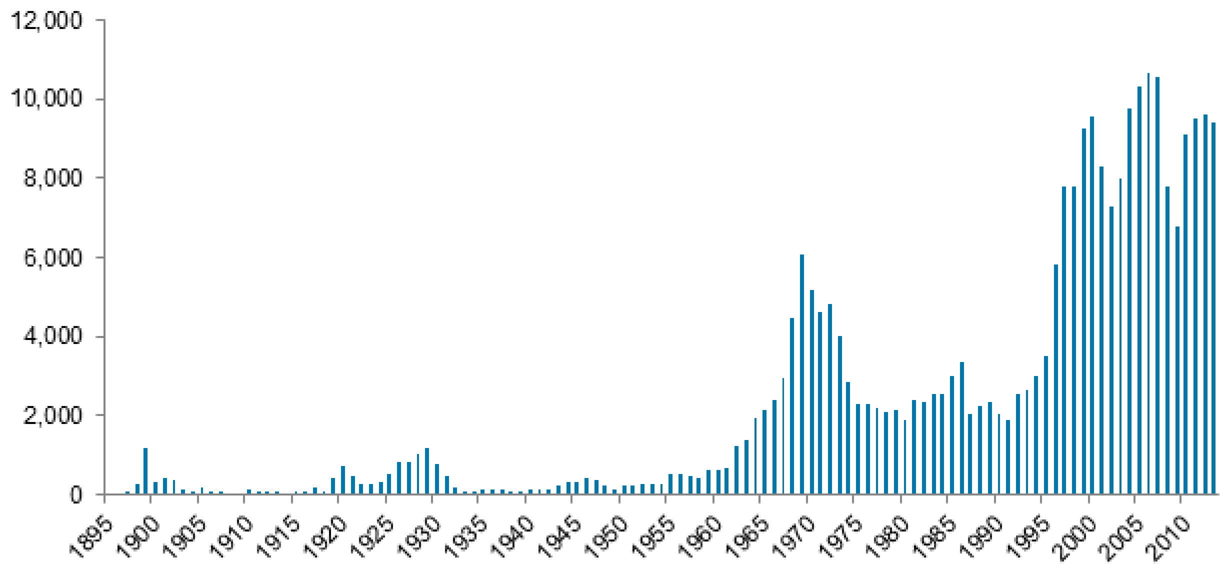
This paper explores the field of mergers and acquisitions. I utilize the cosine similarity measure to measure knowledge relatedness between the acquirer and target, incorporating the knowledge flows between the acquirer and target from the patent text data of both acquirer and target. Utilizing a dataset of 107 M&A's in three high-technology industries and the Knowledge-based view of the firm, I conclude that even though cosine similarity did not predict an M&A transaction being completed or withdrawn, cosine similarity had a positive impact on the post-acquisition performance of acquirer in the short term. My paper discusses the findings along with the limitations and suggests a future research agenda.

Keywords: Mergers & Acquisitions, Event Study, Cumulative Abnormal Returns, Cosine Similarity, Knowledge-Based View of the Firm.

1. Introduction & Motivation

Firms worldwide use "Mergers & Acquisitions" (M&A) to bolster their position in the market, as well as increase shareholder wealth. The high-velocity environment (Eisenhardt, 1989) prevalent in high technology industries along with the quest for new technology makes firms in high technology industries lookout for firms that they can acquire or merge to increase their intellect and knowledge base. Mergers are legal transactions in which two entities are consolidated into a single entity, whereas acquisitions are legal transactions in which one firm takes ownership of other company's stock. In most acquisitions, a "larger company" acquires the "smaller company.” One of the main differences of a merger and acquisition is that a merger results in the formation of a new entity whereas acquisition results in the acquirer gaining control over the target. The company which is acquiring another company is called the “acquirer,” whereas the company being acquired is called the “target.” One of the main aims of M&A is to increase the shareholder returns for the acquirer by generating synergies (Homberg, Rost, & Osterloh, 2009). Prior studies on M&A have investigated different types of relatedness-based measures between acquirer and target such as business relatedness, cultural relatedness, technology relatedness, and knowledge relatedness and their impact on the financial performance of the acquirer. I argue that knowledge relatedness between acquirer and target based on cosine similarity, which is a textual based similarity measure between the acquirer and target, can be a useful measure for predicting success or failure of an M&A transaction. I also argue that higher cosine similarity between the acquirer and target can lead to the better financial performance of the acquirer in the short-term post-acquisition. Subsequent analyses did not find evidence to support cosine similarity predicting the success or failure of an M&A transaction. However, I find substantial evidence to support my argument that higher cosine similarity between the acquirer and target can lead to the better financial performance of the acquirer in the short term. Finally, the paper discusses the limitations and proposes an agenda for future research.

Figure1. M&A transactions in the United States from 1895 to 2014. Source: Adopted from Cretin et al. (2015).



1.1. M&A Transactions in the United States Over the Years

Historically, the activity of Mergers & Acquisitions in the United States market have been cyclical and can be described by the pattern of waves (Martynova & Renneboog, 2008). The M&A transactions in the United States Market over the period 1895 to 2014 can be represented by six waves (Figure 1). The first wave started at the end of the 19th century, characterized by significant technological, economic, and industrial advancements and ended around the year 1904. The second wave started around the end of the first world war and concluded in 1929 due to the stock market crash. The third wave started around the 1950's period which saw the horizontal diversification that created in the formation of corporate giants and ended in the early 1970s due to the energy crisis (Cretin et al., 2015). The beginning of the 1980s saw the formation of the fourth wave characterized by numerous changes such as the financial market deregulation. The fourth wave ended in the year 1987, around the time of the stock market crash. The year

1993 saw the formation of the fifth wave, which was characterized by technological innovation and deregulation. The fifth wave came to an end in the year 2000, which can be attributed to the Internet bubble (Cretin et al., 2015). The sixth and final wave started in the year 2003 and ended with the financial crisis in the year 2008.

On analyzing the M&A transactions worldwide over the past 15 years, we can notice that Mergers & Acquisitions have been gaining prominence as evidenced by the high number of M&A transactions and high M&A value worldwide (Figure 2, 3). The total amount of M&A transactions was listed at $4400 billion in the year 2018 (Figure 2).

Figure 2. M&A Transactions Value Worldwide Over the Past 15 Years. Source: Szmigiera (2018).

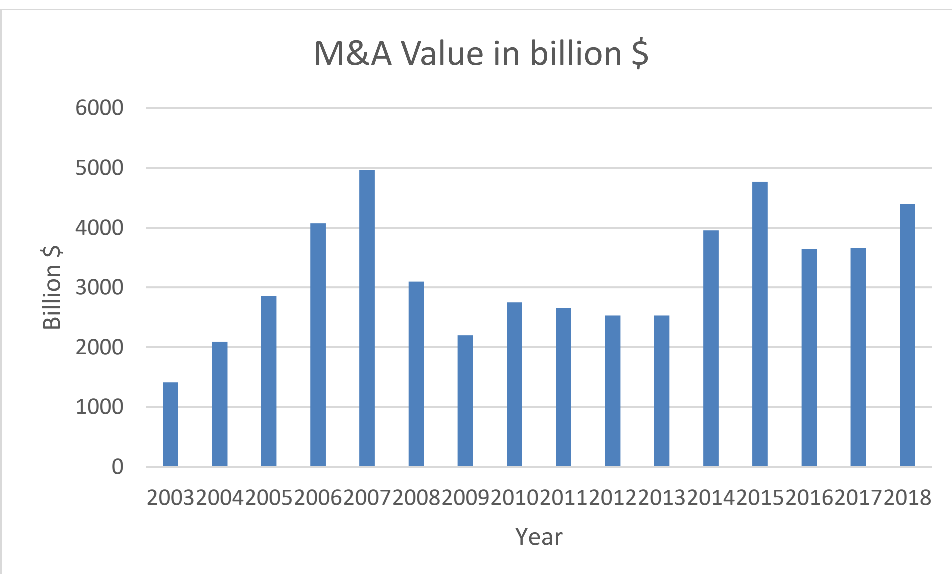
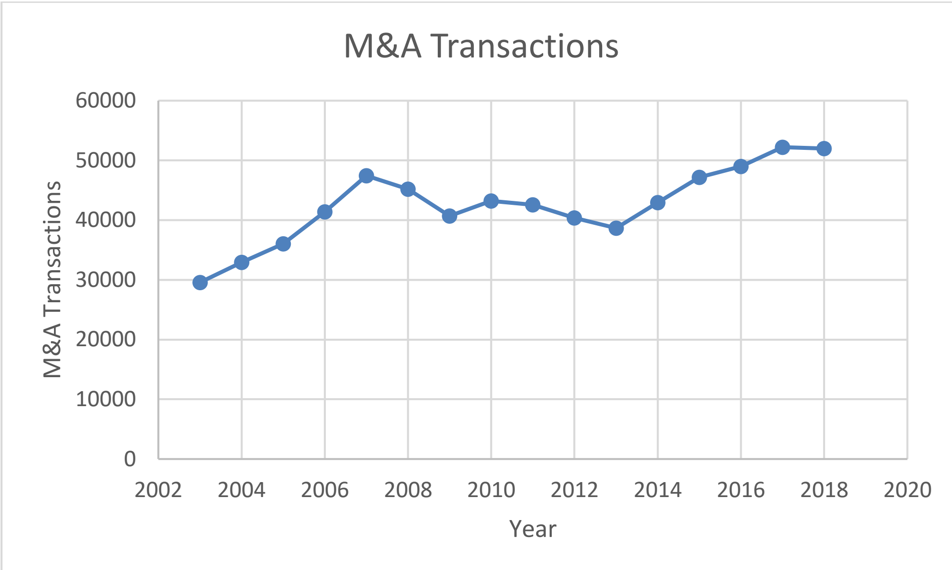


Figure 3. M&A Transactions Worldwide Over the Past 15 Years. Source: “M&A Statistics”(2018).



As evident from figures 2 and 3, mergers and acquisitions were on a steady rise until the year 2007. Due to the economic recession and its aftereffects, the period 2008-2013 was relatively idle in the number of M&A transactions worldwide. After the year 2014, the number of M&A’s are on the rise again, which amplifies the importance of my study.

There are many reasons as to why companies acquire and merge with other companies. One of the most important reasons companies acquire and merge with other companies is to expand their knowledge and capabilities base (Hitt, Bierman, Uhlenbruck, & Shimizu, 2006). Another reason that attracts companies to merge and acquire other companies is to enter new markets without going through the difficulty of establishing a new entity or negotiating with a partner to develop cooperation (Koi-Akrofi, 2016).

1.2. Success of M&A's:

Historically, most M & A deals tend to fail, as indicated by numerous empirical studies (Cartwright & Schoenberg, 2006). Extant literature on the subject lists various reasons as to why mergers and acquisitions do not go as well as planned. After an M&A deal is completed, the target firm usually experiences positive returns in the short term, while the acquirer firm experiences negative returns (Agrawal & Jaffe, 2000).

While the number of failure rates in M&A vary according to various studies, there is a consensus among managers and researchers that failure rates in M&A transactions are high. M&A failure rate is between 40%-50% both in the United States of America and Europe (Koi-Akrofi, 2016). Among the primary reasons for M&A failures are the cultural, behavioral, and psychological factors of employees that become part of the newly acquired or merged firm. Studies such as the one by Gertsen & Soderberg (1998) argue that employees assert their own social identities when they are impacted by cultural differences that arise from changes in management styles or organizational structures. Other studies point towards the apparent apathy of the organization towards employees (Marks & P. H. Mirvis, 1982). Cartwright & Schoenberg (2006) shed light on other factors contributing to M&A failure such as management trying to maximize their gains in terms of what's most beneficial to them as opposed to increasing shareholder wealth, the overvaluation of the target as shown in an empirical study (Anju, Kean, & Richardson, 2000), and the management involved in M&A transactions not learning from the vast body of published research available.

I argue that knowledge relatedness based on the technological similarity of patents between acquirer and target as measured by cosine similarity can be used to predict success or failure of an M&A transaction and that M&A transactions with higher cosine similarities can lead to the better financial performance of the acquirer post-acquisition in the short term.

The relevance of my study stems from the fact that if cosine similarity can be found to be a useful measure of predicting success or failure of M&A transaction and can lead to better short term performance of the acquirer, investors can invest into M&A deals with higher cosine similarities as opposed to ones with lower cosine similarities.

2. Literature Review

The importance of the field of M&A's is signified by the vast amount of research done in the area over the past three decades, encompassing various disciplines of management, such as finance, strategic, behavioral, and operations (Cartwright & Schoenberg, 2006). Majority of the M&A literature focuses on financial studies, while human and psychological studies have been gaining traction recently. The financial-based M&A studies focus on whether M&A activities lead to wealth creation or wealth destruction. While most of the acquisitions lead to negative abnormal returns or abnormal returns that are not significantly different from zero for the acquirer (Agrawal & Jaffe, 2000), there is a significant deviation between acquisition performances at the level of the firm (Cartwright & Schoenberg, 2006). Research into the antecedents of the variation of acquisition performances is at the core of M&A research.

The focal point of strategic management research in M&A's is into the identification of strategic factors and process factors that can explain the deviation of performance between acquisitions. Within the strategic management research literature on M&A's, the literature on "strategic fit" deals with the relationship between the performance and strategic characteristics of the firms involved in the transaction such as "relatedness" (Cartwright & Schoenberg, 2006).

The “process” literature on M&A’s focuses on the role of integration strategies and acquisition processes such as the negotiation and integration process. Scholars in this area of research have pointed towards wrong decision making, along with improper negotiation processes as the reasons for poor acquisition performance.

The cultural dynamics field of M&A’s captures the cultural and behavioral aspects of employees involved in M&A’s. Poor fit of culture between the two firms involved and lack of compatibility in culture are some of the reasons attributed by researchers in the failure of M&A’s.

Recently, there have been some studies highlighting the use of textual analytic techniques for measuring the technological similarity between patents. A recent paper in this direction is the paper by Arts, Cassiman, & Gomez (2018) who utilized Jaccard similarity as a measure of textual similarity between patents, and compared it against USPTO based classification codes. The results conclude that the Jaccard similarity can be a useful measure for the technological similarity between patents.

My paper incorporates the strategic management literature on fit in M&A’s and relatedness along with a text similarity measure, known as the “Cosine Similarity” measure to relate with the post-acquisition performance of the acquirer, and the status of the transaction being completed or withdrawn.

As my study focuses on knowledge flows between the acquirer and targets, based on the text similarity between the patents from the firms, the literature review table below details the literature on relatedness and knowledge flows between firms in the field of M&A’s. The Cosine Similarity section under Data & Methodology explains in detail the reasoning behind the use of cosine similarity measure.

Table 1. Relatedness Literature in M&A's with Sample, Variables, and Results.

Number	Study	Relationship Studied	Sample and data	Variables	Result
1	Kusewitt (1985)	Factors of Acquisition Strategy, Firm Performance	One hundred thirty-eight acquiring firms which completed 3500 acquisitions during the 1967-1976 period.	Performance measured using ROA (%), and Market return (%). Industry Commonality, Acquiree Profitability, Relative size of the firm, and other related size measures used as independent variables.	Industry Commonality and Acquiree profitability were positively related to financial performance. Other factors such as relative size, acquisition rate was negatively associated with financial performance.
2	Pennings (1994)	Organizational Learning, Diversification	Unit of analysis is individual expansion projects. The sample size is 462 from 14 large firms in the non-financial domain in the Netherlands in the period from 1966 to 1988.	Diversification, Location, Mode, Ownership, Expansion Experiences	Expansions were more constant when they were related to the core skills of a firm and arising from the acquisition. Firm's prior diversification activity leads to expansions lasting longer.
3	Gugler K (2003)	International comparison of the effects of mergers.	Merger data of 69605 merger announcements from 1981 to 1998 gathered from Global Mergers & Acquisitions database	Number of deals, Average deal value (Mn$), Country, period split into five parts.	Mergers that result in increased efficiency of both the merged firms via relatedness can result in improved profits and sales for the acquirer.
4	Cloodt, Hagedoorn, &	Innovative Performance	2429 M&A events from	Post-M&A innovative	For non-technological

	Van Kranenburg(2006)	of Companies in high-tech industries.	the period 1985-1994.	performance, Number of non-technological, and technological M&A's, Absolute size of the acquired knowledge base, Relative size of the acquired knowledge base.	M&A's, the acquirer's post-M&A innovative performance is negatively impacted. For technological M&A's, the acquired base of knowledge reduces the innovative performance of the acquirer.
5	Slangen (2006)	Cultural relatedness, Firm Performance	One hundred two cross-border acquisitions by 96 Dutch firms in 30 countries between the period 1995 to 2001.	Acquisition performance, Cultural distance, post-acquisition integration.	Significant differences in the national culture between the acquirer and target reduces acquisition performances in foreign acquisitions when there is tight integration between the acquirer and target, but augments acquisition performances if the integration between the firms is at a lower level.
6	Stahl & Voigt (2008)	Cultural relatedness, Firm Performance	A meta-analysis of 46 studies. The total sample size of M&A is 10710.	Sociocultural integration success or failure, CAR, ROA, National cultural distances.	Effects of Cultural differences on M&A performance varies depending on the degree of relatedness.
7	Capron & Mitchell	Knowledge Sourcing,	Twenty-five field	Interview Study	The decision of whether to use

	(2000)	Firm Performance	interviews of corporate development executives from 12 telecom operators in Europe.		existing knowledge bases or seek external knowledge depends on the knowledge gap between the knowledge required and the knowledge possessed by the firm, and the degree to which the required knowledge is subjected to the failure of the market.
8	Puranam & Srikanth (2007)	Technology Acquisitions, Firm Performance	97 acquisitions from 43 acquirers.	Acquirer's success, Structural integration, acquired firm size and age, technological relatedness, acquirer size and R&D intensity.	Acquirers can benefit from technological acquisitions by leveraging the existing knowledge bases of the acquired firm.
9	Cassiman, Colombo, Garrone, & Veugelers (2005)	Technological relatedness, R&D process.	31 M&A deals from 62 firms in the medium and high-tech industries over 15 years.	Technological relatedness, R&D input, R&D output, R&D performance.	Acquirers and targets with complementary technologies resulted in better R&D performance and efficiency post-acquisition, whereas M&A transactions that are technologically substitutive had a negative impact on R&D performance.

10	Heeley, King, & Govin (2006)	R&D investment, Acquisition Likelihood	1443 acquired firms.	Acquisition status of the firm, Industry adjusted R&D stock measure.	R&D investments can predict the likelihood of acquisition.
11	Larsson & Finkelstein (1999)	Synergies in M&A's, Relative size of the firm.	61 M&A cases from the United States & Europe.	Synergy realization, the relative size of the firm, Organizational Integration, Employee resistance, Management Style Similarity.	M&A success can be measured in terms of synergy realization. Organization integration was a highly important factor concerning synergy realization. Relative size is an essential factor for selecting potential targets.
12	Hitt, Hoskisson, Ireland, & Harrison (1991)	R&D intensity, Firm Performance.	One hundred ninety-one acquisitions completed from 1970 to 1986, covering 29 industries.	R&D Intensity, Industries, Acquisitive growth, Patent Count, ROA	There is a decline in innovation output after the acquisition, and there is a negative relationship between ROA and R&D activities.
13	Moeller, Schlingemann, & Stulz (2004)	Firm Size, Firm performance.	12023 acquisitions from public firms during the period 1980 to 2001	Abnormal returns, firm size	Small-sized acquirers gain around two percentage points higher in announcement returns compared to large-sized acquirers after controlling for the form of financing and public or private status of the company.
14	Makri, Hitt, & Lane (2010)	Knowledge relatedness, Technology relatedness	95 high technology M&A's covering the drug,	Invention quantity, invention quality, Science	Complementarities in scientific and technical knowledge lead to better post-merger

			chemical, and electronic industries in the year 1996.	Relatedness, Technology Relatedness.	invention performance.
15	Homberg et al. (2009)	A meta-analysis of acquisition studies.	67 prior M&A studies.	Business relatedness, Cultural relatedness, technology relatedness, size relatedness, shareholder value, Accounting Performance.	Business and technological relatedness leads to positive effects on overall acquisition performance. Size relatedness and cultural relatedness show an overall negative impact on acquisition performance. The absolute size of the acquirer is a significant factor as smaller firms have a better probability of benefiting from acquisitions.
16	H. Singh & Montgomery (1987)	Relatedness in acquisitions and financial performance.	One hundred five acquisitions with a market value greater than $100 million for the period 1975 to 1980.	Related acquisitions, Unrelated acquisitions, Related single-bid acquisitions, Unrelated single-bid acquisitions.	Related acquisitions lead to higher dollar gains in comparison to unrelated acquisitions.
17	Salter & Weinhold (1978)	Diversification and Acquisition	Thirty-six diversified manufacturers over four years.	ROA, ROE, Related business diversifier, Unrelated business diversifier.	Stockholder benefits mainly arise from related diversifications.
18	Datta DK (1991)	Management Style, Acquisition	One hundred seventy-three acquisitions	Differences in management style,	Differences in the top management styles resulted in a

		Performance.	from the United States Manufacturing Sector valued at $1 million or higher during the period January 1980 to March 1984.	Differences between reward and evaluation systems, Post-acquisition integration, the relative size of the firm, acquisition performance.	negative effect on acquisition performances.
19	Jaffe & Trajtenberg (1999)	International knowledge flows from patent citations.	Analyzes cited patents between the period 1963 and 1993.	Potentially cited patents, Average citations per patent, fraction of self-cites, potentially citing patents.	Patents published from the same firm were more likely to cite each other. Patents published within the same industry were more likely to cite each other.
20	Alcácer & Gittelman (2006)	Patent citations made by examiners and knowledge flows.	Patents granted between January 2001 to August 2003. The sample size included 442,839 citing patents and 5,434,483 cited patents	Organizational, technological, geographical, temporal	About two-thirds of citations are added in by examiners.
21	Lubatkin & Srinivasan (1997)	Shareholder value and large mergers	Two hundred eighty-nine large mergers between the period of January 1980 and December 1987.	SIC merger relatedness index, Abnormal returns.	Mergers of the 1980s were similar in value creation compared to the previous decades.
22	Palepu (1985)	Diversification strategy, entropy, profit	Segment sales data from 1973 to 1979. Thirty firms from industry group food	Jacquemin-Berry entropy measure of diversification, Related product	There is no significant difference between low diversification firms and high

			products.	groups, unrelated product groups, ROS (Return on Sales).	diversification firms in terms of profitability.
23	Kogut & Singh (1988)	National Culture, Entry Mode.	228 acquisition entries to the United States	Choice of entry, diversification, Multinational Experience, Size of Asset	Selection of entry mode is highly influenced by culture.
24	Breschi, Lissoni, & Malerba (2003)	Knowledge-relatedness & Related diversification	Patent applications filed at the European Patent Office from 1982 to 1993.	Knowledge relatedness, Technological relatedness	Knowledge relatedness is highly related to the innovative activities of the firm.
25	Scherer (1982)	Growth in productivity, technology flows between industries	1974 Line of the business survey by FTC that includes data from 443 large corporations in the United States.	Total factor productivity growth, R&D	Productivity slump in the 1970s cannot be attributed to a lack of output from R&D.
26	Jaffe (1987)	Technological Position, R&D productivity	US patents granted between 1969-1979.	Technological group, R&D productivity.	Distribution of patents of a firm across the patent classes can show the technological position of firms.

On reviewing the M&A literature concerning the post-acquisition performance for the acquiring and acquired companies, the term "relatedness" is a term that is commonly used in many papers. Relatedness can be explained as the degree or extent to which two firms are similar (Lubatkin & Srinivasan, 1997). It has been argued by many scholars that the relatedness or similarities between the acquirer and target firms can generate synergies between the firms involved, which can lead to better acquisitions that can create value for the shareholder, while some researchers find support for the negative impact of relatedness on acquisition profitability (Homberg et al., 2009).

Relatedness between acquirer and target firms can be classified into business relatedness, cultural relatedness, technological relatedness, and size relatedness (Homberg et al., 2009). The meta-analytic paper by Homberg et al. (2009) is an analysis of 67 prior M&A studies and does an excellent job at explaining the different types of relatedness and their effect on acquisition performance. The meta-analytic paper reported that business relatedness and technological relatedness lead to overall positive acquisition performance, while cultural relatedness and size relatedness lead to overall negative acquisition performance.

2.1. Business Relatedness

In the field of M&A, business relatedness is concerned with the acquisitions in comparable markets and industries, with the aim of transferring knowledge from the target to the acquirer (Homberg et al., 2009). The results from empirical studies relating business relatedness to firm performance show both positive and negative effects. The transfer of existing knowledge can result in operational synergies, and a reduction in unit costs (H. Singh & Montgomery, 1987). From the literature on M&A's, both subjective and objective ways can be utilized to measure business relatedness. The first measure of business relatedness is a diversification index which can be calculated based on the two digits and four-digit SIC (Standard Industrial Classification) code of companies (Homberg et al., 2009). The second measure of business relatedness is an entropy-based measure of the two digits and four-digit SIC code and combining the Herfindahl-Index (Palepu, 1985). The third measure of business relatedness is the similarity of the SIC index between the acquirer and target of paper known as the industry commonality (Kusewitt, 1985).

The fourth measure of business relatedness is subjective based measures as they are based on surveys or opinions of experts (Homberg et al., 2009). The paper by H. Singh & Montgomery (1987) used a sample of 105 acquisitions with market value greater than $100 million during the time period 1975-1980 and split the data into related acquisitions and unrelated acquisitions where related acquisitions are defined as the acquisitions that are based in the same line of production and research or based on similar markets. Using abnormal returns as a performance measure, H. Singh & Montgomery (1987) reported that related acquisitions lead to more profitability in comparison to unrelated acquisitions. Salter & Weinhold (1978) utilized a sample of 36 diversified manufacturers over four years and classified the diversifications as business-related if the diversifications were in the same market or based on similar production technologies or scientific research, and the rest as unrelated. Utilizing ROA (Return on Asset) and ROE (Return on Equity) as performance measures, Salter & Weinhold (1978) reported that related diversifications via acquisitions between 2 firms could result in risk reduction due to the stable income flows generated when acquisitions are in similar markets or industries. Kusewitt (1985), and Pennings (1994) are some of the other studies that show positive effects of business relatedness using ROA as a dependent variable. The study by Kusewitt (1985) utilized a sample of 138 acquiring firms totaling 3500 acquisitions during the period 1967-1976. Utilizing the industry commonality between the acquirer and target, which is the percentage of assets acquired which fall in the same 2 digit SIC code as a measure of business relatedness, along with ROA, and Market return as performance measures, Kusewitt (1985) reported that industrial commonality was positively related to financial performance, while factors such as relative size, and acquisition rate was negatively related to financial performance. The study by Pennings (1994) included a sample of 462 expansion projects from 14 non-financial firms in the

Netherlands during the period of 1966-1988. This study utilized the variable diversification relatedness based on the similarities in the SIC code of the acquirer and target, location, expansion experiences which was 3 or 5 years moving average of the longevity of previous projects (Pennings, 1994). Pennings (1994) reported that expansions were more constant when they were related to the core skills of a firm and arising from the acquisition and that a firm's prior diversification activity lead to expansions lasting longer. Gugler K (2003) studied M&A's worldwide utilizing a data set comprising of 69605 merger announcements from the years 1981-1998 with the variables number of deals, average deal value (in Millions of $), country, and reported that improved efficiencies are realized for firms with better relatedness, which can lead to better sales and profit for the acquirer.

2.2. Cultural Relatedness

Cultural relatedness refers to the similarity in corporate culture or management styles between two entities. Cultural relatedness can lead to positive firm performances due to the synergies in decision-making processes and other organizational factors (Datta DK, 1991). Cultural relatedness can be measured by three different measures. The first measure of cultural relatedness is a national cultural index following the approach of Kogut & Singh (1988). The second measure of cultural relatedness can be the use of bivariate variables that can differentiate between domestic and foreign acquisitions, and finally, the use of subjective measures such as survey questionnaires form the third measure of cultural relatedness (Homberg et al., 2009).

The study by Datta DK (1991) utilized a sample of 173 acquisitions from the United States Manufacturing Sector valued at $1 million or higher during the period January 1980-March 1984 and reported that differences in the top management styles had a negative effect on acquisition performances. Also, the costs of integration are considerably reduced when culturally related firms are merged or acquired (Larsson & Finkelstein, 1999). In their study, Larsson & Finkelstein (1999) analyzed 61 M&A cases from the United States & Europe and utilized relative size of firm, organizational integration, employee resistance, management style similarity as independent variables and synergy realization of M&A as a performance measure as it is dependent on actual performance and avoids the common problems associated with event studies. Larsson & Finkelstein (1999) measured synergy realization by adding up 11 items in a survey that analyzes the responses to synergies realized by the M&A in various domains such as consolidated purchases, production, and marketing, transfer and creation of technologies. The organizational integration measure was computed by adding up 2 items representing the interaction of firm and effort in coordination, while employee resistance was calculated by taking the mean of 2 items related to the resistance of employees in the first half and the second half, the management style similarity was estimated by one item that describes management similarities between 2 firms in terms of formality and employee participation, and relative size was measured by dividing the annual sales of the acquirer to the yearly sales of the target in the year of merger or acquisition. The findings of Larsson & Finkelstein (1999) convey that organizational integration is a very crucial factor and positively impacts synergy realization, i.e., higher organizational integration leads to higher synergy realization, and the relative size of the firm was also an essential factor in selecting targets.

Some empirical studies, such as the one by Slangen (2006) have provided support for the positive effect of cultural relatedness on firm performance. The study by Slangen (2006) utilized a sample of 102 cross-border acquisitions from firms based in the Netherlands in 30 countries. This study used the cultural distance as based on the Kogut & Singh (1988) index to measure cultural relatedness, a questionnaire provided to managers on post-acquisition performance in the first 2 years after acquisition based on the criteria of sales, market share, profit, and overall performance to measure the acquisition performance, a questionnaire provided to managers on the intended amount of autonomy that the management team would provide to the acquired firm at the time of acquisition following Datta DK (1991) to measure the integration post-acquisition and concluded that considerable differences in the national culture between the acquirer and target reduces the acquisition performances in foreign acquisitions when there is tight integration between the acquirer and target, but augments acquisition performances if the integration between the firms is at a lower level (Slangen, 2006). A meta-analysis study by Stahl & Voigt (2008) reported mixed results on the effects of cultural relatedness using national cultural differences as the independent variable and Cumulative Abnormal Returns (CAR) and ROA as the performance measure. Stahl & Voigt (2008) utilized a sample of 46 M&A studies totaling 10710 transactions.

2.3. Technological Relatedness

Technological relatedness between two firms can arise from similarities in technology and innovation (Homberg et al., 2009). Technological relatedness can lead to achieving synergies between acquirer and target from similar or complementary operations (Larsson & Finkelstein, 1999). Similar transactions between the two firms can lead to synergies via unit costs reduction and efficiencies gained as a result of not having to consume resources on learning, and the combination of complementary technologies can also be a source of synergies. (Homberg et al., 2009).

Technological relatedness can be measured using 3 ways, as described in (Homberg et al., 2009): The first measure is found out by calculating a diversification index that is based on the similarities of the IPC (International Patent Class) classes of the patents at the level of 3 digits possessed by the companies involved , the second measure of technological relatedness utilizes patents as a source of knowledge base and is computed by the list of patent numbers commonly appearing in the knowledge bases of the acquirer and target. The third measure is a list of subjective measures that are reliant on the opinions of experts.

The study by Puranam & Srikanth (2007) utilized a sample of 97 acquisitions from 43 acquirers with technology relatedness measured by the overlap in technology codes between the acquirer and target as given by the SDC platinum. This measure of technology relatedness was calculated as the number of common technology codes between the acquirer and target divided by the total number of technology codes by the acquirer (Puranam & Srikanth, 2007). This study concluded that acquirers could benefit from technological acquisitions by leveraging the existing knowledge bases of the acquired firm (Puranam & Srikanth, 2007). The study by Cassiman et al (2005) utilized a sample of 31 M&A deals from 62 firms in the medium and high-tech industries over a period of 15 years, and reported that acquirers and targets with complementary technologies resulted in better R&D performance, and efficiency post-acquisition whereas M&A transactions that are technologically substitutive will have negative impact on R&D performance. Cassiman et al. (2005) distinguished themselves from other studies by providing a survey questionnaire to the managers to assess the technological relatedness based on the criteria that the firms were classified as having overlap in technical strength if both firms had R&D projects in the same technological field before the M&A transaction. If the firms were in different fields of technology but the technological knowledge could be transferred to other R&D

activities of the acquirer, it was classified as complementary technological strengths (Cassiman et al., 2005).

2.4. Size Relatedness

In the field of M&A, size relatedness refers to the similarity of size between the acquirer and target. There are two ways by which size relatedness can be measured. The first measure of size relatedness is the ratio of target size to acquirer size, as given by assets, sales, revenues, or the number of employees, and the second measure of size relatedness is provided by subjective criteria such as survey questionnaires or expert opinions (Homberg et al., 2009). Some researchers have argued that the similarity in size between acquirer and target can lead to better efficiencies in integration arising from the ability of the acquirer to grasp and apply the knowledge acquired (Homberg et al., 2009). In contrast, some researchers argue that differences in size can lead to better synergies between the two firms (Homberg et al., 2009). For example, a smaller acquirer acquiring a larger target can be beneficial due to the increased market power and economies of scale realized by the acquirer, and larger acquirer acquiring a smaller target can be related to better performance arising from the simplicity in the organization structure of the target which results in easier integration. Furthermore, the absolute size of an acquirer is an crucial factor in acquisitions and acquirers smaller in size have a higher probability of profitability in M&A’s (Homberg et al., 2009). Moeller et al (2004) studied the relationship between firm size and firm performance as measured by abnormal returns with a sample of 12023 acquisitions from public firms in the time period 1980-2001 and reported that small-sized acquirers gained around 2 percentage points higher in announcement returns compared to large-sized acquirers after controlling for form of financing and public or private status of the company. Overall, the research on the relationship between size relatedness and acquisition performance have shown mixed results.

2.5. Knowledge Relatedness

Apart from the four types of relatedness in M&A research as per Homberg et al. (2009), knowledge relatedness is of great interest in the field of M&A. Knowledge relatedness can be defined as the relatedness in knowledge bases between two firms (Makri et al., 2010). As firms in similar technological fields can have similar or complementary knowledge bases which can be shared, this relatedness in technological areas can be used as a proxy measure for knowledge relatedness, and firms with similar technology relatedness can be a better target for acquisition (Makri et al., 2010). The study by Makri et al. (2010) utilized a sample of 95 high technology M&A's covering the drug, chemical, and electronic industries in the year 1996, and reported that complementarities in scientific and technical knowledge lead to better post-merger invention performance. Makri et al. (2010) drew upon the work of Larsson & Finkelstein (1999) and used similarities and complementarities in scientific research with the same defined knowledge areas as measures of knowledge relatedness, defined as science similarity, and science complementarity.

Knowledge relatedness can envelop three main concepts: the proximity in knowledge, the commonalities in knowledge, and complementarities in knowledge (Breschi et al., 2003).

The proximity in knowledge can arise from the processes of learning, which can unintended or intended (Breschi et al., 2003). Unintended learning, also known as spillovers in learning, can be defined as the spillover of knowledge in one technology to another related technology, which is initiated by the innovative processes of the firm (Breschi et al., 2003). Intended or local learning can arise from acquirers seeking other firms possessing new technologies or knowledge bases related to R&D, fields of scientific research, etc., that are very similar to the technologies owned by the acquirer (Breschi et al., 2003).

The commonalities in knowledge refer to similar knowledge bases that can be used in different technologies and results in firms achieving “economies of scope” (Breschi et al., 2003). The complementarities in knowledge are related to complementarities in knowledge and technology bases that arise from the use of technologies that are not related to each other but are both required in tandem for the introduction of new products and services (Breschi et al., 2003).

Knowledge relatedness can be commonly measured in 3 ways. The first measure of knowledge relatedness, as introduced by Scherer (1982) measured the knowledge relatedness between 2 firms by the extent of R&D activity in the two firms. The second measure of knowledge relatedness known as the cosine index, as used in Jaffe (1987) can be calculated by finding the correlation between the vectors that represent the patent distribution of firms from diverse technology fields, as indicated by the 12 digit IPC codes (Breschi et al., 2003). The third measure of knowledge relatedness utilizes bibliometrics by finding the recurrence of classification codes designated to patent documents (Breschi et al., 2003).

2.6. Performance Measures in M&A

The market-based measures commonly used for measuring M&A success are abnormal returns via Cumulative Abnormal Returns (CAR) which are calculated using the event study methodology, growth in earnings per share, and returns of a stock. Accounting based measures commonly employed are the ROA, ROE, or the increase in sales. Apart from the market based and accounting-based measures, subjective measures such as transfer in skill and combination have also been used as performance measures in the M&A literature (Homberg et al., 2009).

2.7. Knowledge flows between firms

The literature review on patent-related analysis shows that prior studies have used patent citations for measuring knowledge flows. For example, Jaffe & Trajtenberg (1999) found that patents within the same patent class were much more likely to cite each other. Alcácer & Gittelman (2006) analyzed the distribution of examiner and inventor citations and argued for the use of patent citations for measuring knowledge flows between examiner and inventors.

3. Data & Methodology

The SDC (Securities Data Company) Platinum M&A database from Thomson Reuters was used to collect the worldwide mergers and acquisitions data from publicly listed firms in 3 high tech industries: Pharmaceutical, Software, and Telecommunications over the years 1987 to 2017. The three industries were selected as these industries file for many patents and are involved in many Mergers & Acquisitions. From the three high tech industries, only companies (both acquirer and target) with deal values $200 million and higher were considered. The data extracted from SDC Platinum also provided other information such as the status of the transaction (Completed or Withdrawn), % owned before and after the transaction, target CUSIP (Committee on Uniform Security Identification Procedures) number and acquirer CUSIP number.

The data extracted from SDC Platinum comprised of 1659 M&A’s. The CUSIP numbers obtained from SDC platinum database for both acquirer and target were converted to PERMNO (Perm Number), which is a unique and permanent identifier assigned by the Wharton Research Data Services (WRDS) to companies. The CUSIP numbers were converted to PERMNO as the

CUSIP numbers from SDC platinum, and WRDS platform does not match. The permanent identifiers such as PERMNO for companies assigned by WRDS do not change over time. The conversion of CUSIP from SDC platinum to PERMNO resulted in the reduction in the number of Mergers & Acquisitions to 407.

The resultant M&A dataset was used to obtain patent data for each target and acquirer pair from the patent data website, http://www.freepatentsonline.com/ as used in prior patent-related studies (Fabian, Wächter, & Schroeder, 2012). Python programming language was used to scrape patent data from the free patents' website using the package Beautiful Soup. The patent data extracted for each firm comprised of title, abstracts, published year and cited references.

The Event Study platform from WRDS was used to obtain the performance measure (Cumulative Abnormal Return), for the acquirer and target firms at the announcement dates, as consistent with the literature. The CAR was also computed for the acquirer one year before and after the announcement date to calculate the prior and post-financial performance of the acquirer. As my study requires that both the target and acquirer have patent text data, as well as CAR at the announcement date, 1 year before the announcement date and 1 year after the announcement date, and the fact that the patent text data, and performance (CAR) data were not available for some companies, the M&A dataset was further reduced from 407 to 107.

The final dataset comprised of 107 M&A data points, of which 95 transactions were completed, and 12 were withdrawn. The number of employees and net sales was extracted for the acquirer and target firms using the COMPUSTAT database in WRDS.

Table 2. Mergers & Acquisitions Count by Industry

Industry	Number of Mergers & Acquisitions
Pharmaceutical	23
Software	72
Telecommunications	12

In the final data set, the software industry had the highest number of mergers & acquisitions, followed by telecommunication and pharmaceutical (Table 2).

3.1. Robustness Check:

The Cumulative Abnormal Return (CAR) of the acquirer and target at the announcement date were compared to check if the M&A data in my study was comparable to prior M&A studies. The literature on M&A shows that typically after an M&A deal is announced, the target firm on average gets higher expected abnormal returns in comparison to the acquirer, as investors reward the target for being acquired. For comparing the CAR of the target to that of the acquirer at the announcement date, the Paired sample t-test, and the Wilcoxon signed-rank test were conducted. These tests were chosen as the acquirer and target are part of a dyadic relationship, and hence do not comprise of an independent sample. Both parametric and non-parametric tests were conducted for comparing CAR of the acquirer and the target at the announcement date for validation purposes.

Table 3. Paired Sample T-Test (Comparing CAR of acquirer and target at announcement date)

Paired Difference	Mean	Std. Dev	Std. Error Mean	95% LCL	95% UCL	t	df	Sig. (1-tailed)
Carnntar - Carannacq	0.771	1.266	0.122	0.528	1.014	6.301	106	3.4423E-9

Caranntar stands for CAR of the acquirer at the announcement date, and Carannacq stands for the CAR of the target at the announcement date. From the paired sample t-test results (Table 3), we have sufficient evidence to reject the null hypothesis that there is no mean difference between Carnntar and Carannacq (P-value = 3.4423E-9). As the paired difference Caranntar – Carannacq is positive, we can infer that the Caranntar is significantly higher than Carannacq, and the mean difference between Carnntar and Carannacq is 0.771.

Table 4. Wilcoxon Signed-Rank Test (Comparing CAR of acquirer and target at announcement date)

Caranntar - Carnnacq	N
Negative Ranks (Caranntar < Carannacq)	21
Positive Ranks (Caranntar > Carannacq)	86
Ties (Caranntar = Carannacq)	0
Total	107

Table 5. Test Statistic for Wilcoxon Signed-Rank Test (Comparing CAR of acquirer and target at announcement date)

	Caranntar – Carannacq (Negative Ranks)
Z	-6.275
Asymp. Sig. (1-tailed)	1.75E-10

Wilcoxon signed-rank test (Table 4 and 5) was also conducted for the robustness check. For the pair comparison Caranntar – Carannacq, there are more positive ranks than negative ranks, and a P-value of 1.75E-10 with a Z statistic of -6.275 for the negative rank differences implies that the null hypothesis of equal mean ranks can be rejected.

From the paired-sample t-tests and Wilcoxon signed-rank tests, we can conclude that the CAR of the target is significantly higher than that of the acquirer at the date of the announcement, indicating that the M&A dataset is robust.

3.2. Cosine Similarity

Traditionally, technological similarity has been measured in numerous studies using the USPTO (United States Patent and Trademark Office) classification system (Aharonson & Schilling, 2016). Numerous scholars have pointed out the various shortcomings of the USPTO classification system. Some of these include the argument by J. Singh & Agrawal (2011) that the aggregated classification system followed by USPTO might not be able to absorb the different technological characteristics of a patent, and the argument by McNamee (2013) that patents that are technologically similar can end up under different USPTO classifications. Furthermore, the use of such subjective similarity measures such as USPTO or IPC classification codes can lead to bias in the calculation of similarity measures.

Rather than relying on patent citations, patent classification codes or the similarity measures between the classification codes, I have incorporated the text data from patents of both acquirer and target, as the patent data embodies the knowledge base and innovations of the firm. By utilizing textual analytics techniques on the patent text data on both the acquirer and target, a more robust statistical measure was used for the technological similarity between the acquirer and target known as cosine similarity. Numerous scholars have argued that technological similarity between companies based on the similarities in patent content can be used as a proxy for knowledge relatedness (Makri et al., 2010), as companies that have similarities in technologies have related knowledge bases, either through similarities or complementarities.

Due to the limitations of measuring technological similarities between two patents using USPTO and the fact that the specific content of the patents for each firm such as the patent abstracts can be utilized in comparing knowledge across the patents (McNamee, 2013), a text-based similarity measure was used as a measure for technological similarity. A recent study (Arts et al., 2018) used a text-based similarity measure to develop a sample of technologically similar patents filed in the same year. Arts et al. (2018) used the Jaccard index, which is calculated by dividing the length of the intersection of 2 sets by the length of the union of 2 sets. The results were also validated by a panel of 13 selected and paid experts from both industry and academia representing five different areas of expertise, thus providing credence to the use of text-based similarity measures to assess the technological similarity between patents. Instead of the Jaccard index, the cosine similarity measure has been used in my study, which is considered by many researchers to be a more robust similarity measure in comparison. Furthermore, the cosine similarity measure does not depend on the magnitude of the technological field, as measured by the application count of patents (Breschi et al., 2003).

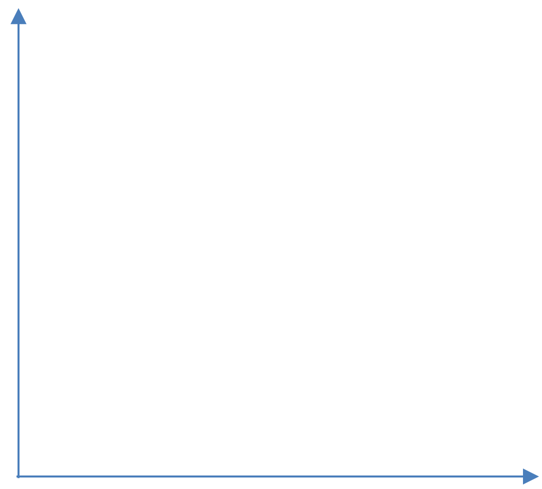
The cosine similarity measure used in my study is different from the cosine index used in Jaffe 1989 and Breschi et al. (2003), in that I utilize the patent text data of acquirer and target, rather than using the similarity in IPC codes for assessing firms that are in the similar technological domain.

"Cosine similarity" can be defined as a similarity measure of an inner product space that measures the cosine of the angle between 2 vectors. For example, for two vectors a and b, the cosine similarity between the two vectors can be found out from the formula:

Cosine Similarity, $\cos\theta = \frac{(a.b)}{(\|a\|.\|b\|)}$. In the formula for cosine similarity, the numerator represents the dot product of the vectors, the denominator represents the product of the length of the vectors, and θ represents the angle between two vectors (Huang, 2008). For example, consider two vectors a and b with the coordinates as [12,10] and [13,16] respectively. In the above case, the length of the vector a is $\sqrt{12^2 + 10^2}$ = 15.62 and the length of the vector b is $\sqrt{13^2 + 16^2}$ = 20.61. The dot product of the 2 vectors is (12*13) + (10*16) = 316. Plugging in the values to the cosine similarity formula, we get:

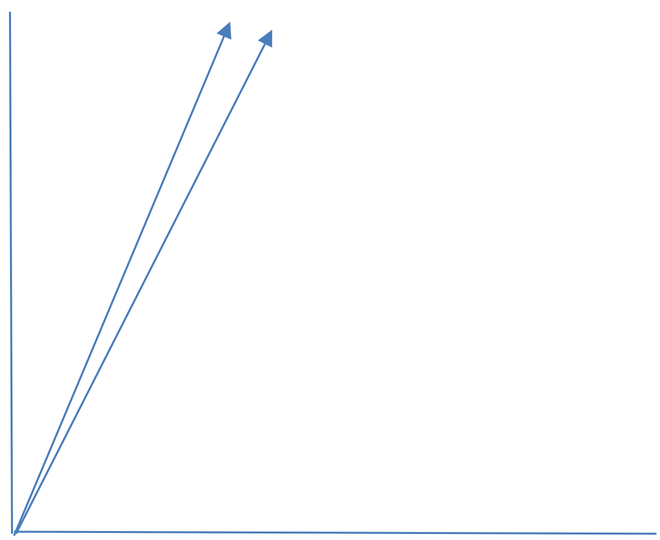
cos θ = [(12*13) + (10*16)] / [15.62*20.61] = 316/321.93 = 0.98. Hence, the cosine similarity between the two vectors a and b for the above example is 0.98. The cosine similarity values from my study are in the range of 0 to 1, where 0 implies that the θ value is 90 degrees (Figure 4), indicating no similarity between the patents and one implies that the θ value is 0 degrees, indicating the patents are identical for both companies.

Figure 4. Orthogonal Vectors (90 degrees between the two vectors).



When two vectors are orthogonal (Figure 4), the θ value is 90 degrees, which means there is no knowledge relatedness between the two companies. When the two vectors are very close to each other (Figure 5), the θ value is very close to 0 degrees, indicating a high degree of knowledge relatedness between the two companies.

Figure 5. The angle between the two vectors close to zero degrees



The following steps were followed to obtain the cosine similarity measure between acquirer and target:

- Scrape patent text data
- Pre-process texts
- Compute TF-IDF scores
- Compute cosine similarities between pairs of companies

After the patent abstracts were downloaded, the resultant abstracts were pre-processed. This pre-processing step included removing punctuation marks, transforming letters to lower case, removing digits, removing stop words, and stemming documents. Stop words are very commonly used words such as “the,” “as,” “if,” etc. which do not add any value to the analysis and hence needs to be removed. Stemming of words reduces the word to its common base root form. For example, the words “develop,” “developing,” and “developed” will be reduced to the common base root form of “develop” after being subjected to stemming. After preprocessing the texts, the TF-IDF (Term frequency-inverse frequency) scores were calculated. The term frequency (TF) indicates the number of times a word occurs in a document. TF assumes that all terms are weighted equally. As all terms are not considered to be equal, the terms more commonly occurring are given lower weight, and the terms that are less frequently occurring are given higher weight by computing the inverse document frequency (IDF). The TF-IDF score can be calculated by using the formula:

TF-IDF = (Number of term occurrences in the document) * log (Number of total documents / Number of documents containing the word).

For example, consider two documents A and B with text data that comprises only two words "tablet," and "software," and with the TF-IDF scores as follows:

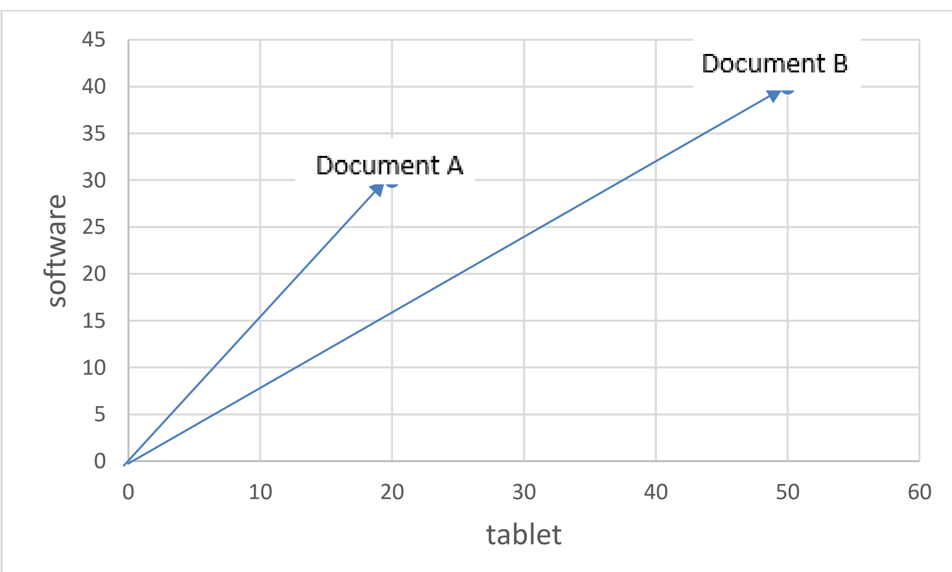
Table 6. TF-IDF Scores Example

	"tablet"	"software"
Document A	20	30
Document B	50	40

The TF-IDF score for the word "tablet" in document A and document B is 20 and 50 respectively whereas the TF-IDF score for the word "software" in document A and document B is 30 and 40 respectively.

The TF-IDF values from the table can be represented in the vector space as follows:

Figure 6. TF-IDF values represented in Vector Space.



The final step comprised of converting the TF-IDF into cosine similarities using the statistical tool Exploratory. The resultant output provided the cosine similarity measure between each pair of company.

Table 7. Example of Cosine Similarity Matrix for 3 Companies.

Company	A	B	C
A	1	0.067	0.025
B	0.067	1	0.032
C	0.025	0.032	1

In the cosine similarity matrix example (Table 7), the cosine similarity between company A and B is 0.067, B, and C is 0.032, and C and A is 0.025. The cosine similarity between a company with respect to itself is 1, as the patents are identical.

3.3. Event Study

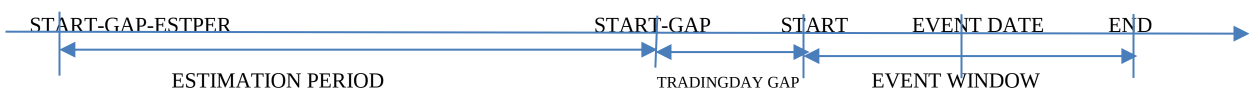
Ever since the first published event study (Dolley, 1933), event studies have been used in numerous empirical studies in finance (Binder, 1998). The main aim of conducting event studies is to analyze the reactions of the stock market to an event at the firm level or market in general. For M&A transactions in general, the announcement date is of high relevance, as the developments before and after the announcement and the reaction of the market to these developments can influence the stock price and hence the returns of the firms involved in the M&A transaction. As an announcement of M&A is done and information made available to the public, investors are expected to react to the announcement and details such as acquiring new technologies and thus impact the firm's returns. Both the time period before and after the announcement date is of interest.

The event study platform under WRDS to calculate the abnormal returns for each firm. First, the user has to develop a text file with the unique identifier listed in one column and the announcement listed in another column with space left between each column. The event study platform accepts three unique identifiers: PERMO, CUSIP, and TICKER. The PERMNO option was selected as the unique identifier for my study. Of the three options for the risk model, the Fama-French Plus Momentum model, also known as the Fama-French four-factor model, was used. The Fama-French Plus Momentum model utilizes the abnormal returns as defined in the Carhart M (1997) model. The formula for abnormal returns from the FF plus momentum model is as follows:

$$AR = R - E(R) = R - (R_f + \alpha + \beta_1 * (R_m - R_f) + \beta_2 * SMB + \beta_3 * HML + \beta_4 * MOM)$$

AR refers to the Abnormal Returns, E(R) refers to the expected return, R refers to the return, R_f is the risk-free rate, R_m denotes the market return, SMB refers to the size, HML denotes value stocks, and MOM denotes momentum.

Figure 4. Event Study Timeline



Following are the event study timeline terminologies as outlined in "Event Study Background" (n.d.):

The user first specifies the estimation window over which the risk model will be estimated. Then the event window must be defined [START, END], as well as the gap between the end of the estimation period and the beginning of the event window. The event date is given as t = 0. For example, consider the estimation period to be 140 days, START and END at -10 and +10, and the gap at 15 days, all measured in relative to the event data (t = 0). In this case, the estimation period will cover the trading days in the range of [-165, -25] and event window in the range of [+10, -10]. The GAP between the estimation period and the event window is required for so that the estimation period does not include information from market leaks before the event.

After the risk model was specified, the estimation parameters were entered. Specifically, WRDS asks for the estimation window, a minimum number of valid returns, gap, event window start, and event window end.

Table 8. Estimation Parameters Utilized for Event Study

Estimation Window	100
Minimum Number of Valid Returns	70
Gap	5
Event Window Start	-15
Event Window End	180

The estimation window was set at 100 days (Table 8) to have a reasonable period for expected return estimation. The minimum number of valid returns refers to the number of non-missing observations of returns that are within the estimation window needed to compute expected return estimates. The minimum number of valid returns was set at 70 days as 70 days is a reasonable number of valid returns and well within the estimation window of 100 days. The gap between the end of the estimation window and the beginning of the trading window was set as five days to reduce the probability of event-induced return variance. The event window start refers to the starting point in reference to the event start date. The event window start of -15 days meant that the event window started 15 days before the announcement date. The event window end of 180 meant that the event window ended 180 days after the announcement date.

3.4. Variables

Table 9. Description of Variables in the Study

No	Variable	Description
1	Status	Completed (1) or Withdrawn (0)
2	Carann	CAR of acquirer at announcement date
3	Carannpreacq	CAR of acquirer one year before the announcement date
4	Carannpostacq	CAR of acquirer one year after the announcement date
5	Caranntar	CAR of the target at announcement date
6	Sameind	Indicates whether an M&A transaction is in the same industry (1) or not (0)
7	Cosine	Cosine Similarity (Range of 0-1)

The variable *Status* denotes whether the M&A transaction was completed or withdrawn. The completed transactions were coded as 1, and the withdrawn transactions were coded as 0. The financial performance measured is the Cumulative Abnormal Return (CAR), computed from the WRDS event study platform using the Famma-French Plus Momentum model. *Carann* refers to the CAR of the acquirer at the date of the announcement, *Carannpreacq* denotes the CAR of acquirer one year before the announcement date, and *Carannpostacq* denotes the CAR of acquirer one year after the announcement date. *Caranntar* refers to the CAR of the target at the announcement date. The variable *Sameind* indicates whether an M&A transaction occurred in the same industry or not. The variable Cosine represents Cosine Similarities between the acquirer-target pairs and is in the range of 0-1.

Table 10. Description of Control Variables in Study

No	Variable
1	Net Sales (In million $)
2	Employees (In thousands)
3	Acquirer Employees / Sales (Normalized Measure)
4	Target Employees / Sales (Normalized Measure)

3.5. Control Variables

Net sales and employees have been used as control variables in prior literature, as they can be used as proxies for firm size (Dang & Li, 2015). I have chosen to incorporate both the number of employees and the sales as controls. But rather than using the employee and sales information directly, I have used a normalized measure, employee/sales, which gives the number of employees per sale of $. As net sales are in millions of dollars and number of employees in thousands from the COMPUSTAT database in WRDS, the normalized measure of employee/sales was found out for both the acquirer and target by utilizing the formula below:

Employee / Sales = (Employee*1000) / (Net Sales*1000000)

Table 10. Descriptive Statistics

Variable	N	Minimum	Maximum	Mean	Std. Dev
Carannacq	107	-2.966	3.041	-0.100	0.838
Carannpreacq	107	-2.162	1.998	-0.019	0.756
Carannpostacq	107	-1.737	3.648	-0.034	0.858
Caranntar	107	-0.967	4.171	0.671	0.896
Cosine	107	0.023	0.604	0.121	0.098
Status	107	0	1	0.89	0.317
Sameind	107	0	1	0.58	0.496
Empacqdiv	100	0.0000007	1.294	0.015	0.132
Emptargdiv	92	0	0.0003	0.00001	0.00004

4. Theory & Hypotheses

Following the seminal work by Penrose (1959), the Resource-Based View of the firm as proposed by Barney (1991), has been widely used in the strategic management literature. RBV states that a firm’s resources and capabilities from a firm that is Valuable, Rare, and Inimitable can lead to sustained competitive advantage (Jay Barney, Wright, & Ketchen, 2001).

The Knowledge-based view of the firm extends the Resource-Based View and states that knowledge is the most important, and significant resource of a firm, as knowledge-based resources and capabilities are difficult to imitate, socially complex, and lead to a sustained competitive advantage, along with exceptional corporate performance (Grant, 1996).

The Knowledge-Based View of the firm is the appropriate theory for this paper, as it is based on knowledge flows between target and acquirer. Based on the above measures, literature review, and theory, the following hypotheses were formed:

Cosine similarity has been regarded as a more robust measure of technological similarity in comparison to USPTO classification. As firms with higher technological similarities are more likely to be within the same industry (example: a drug company acquires another drug company to gain new technology or product and realize synergies), the first hypothesis was developed as follows:

H_1: M&A firms within similar industries will have higher cosine similarities compared to firms across other industries.

Due to the knowledge relatedness arising from the technological similarities between acquirer and target, and as higher cosine similarity can be related to higher knowledge relatedness, I argue that the similarities in knowledge bases can lead to higher chances of completion of the M&A transaction. Hence, the second hypothesis was developed as follows:

H_2: M&A transactions with higher cosine similarities will lead to higher chances of transaction completion.

The post-performance of the CAR of the firm was calculated only one year after the announcement date, as the CAR generally is a short term measure calculated for shorter event windows, and as the daily abnormal returns compounded over long terms can lead to biased results (Brown & Warner, 1985), and the general consensus that short-term horizons provide more reliable results using CAR in event studies (Kothari & Warner, 2007) . CAR is a market-based measure that takes into consideration the reaction of financial investors around the announcement date (Brown & Warner, 1980) and financial investors are more interested in financial gains pertaining to the short-term (King, Dalton, Daily, & Covin, 2004).

Due to higher knowledge relatedness arising from higher cosine similarities between acquirer and target, it can be argued that the acquirer will be better able to integrate and learn from similar and related knowledge bases, thus improving its knowledge-based capabilities (Gold, Malhotra, & Segars, 2001), which can lead to better financial performance in the stock market from positive investor reaction, at least in the short run.

The similarities in knowledge bases between the firms can create a positive reaction among the financial investors in the short run since the knowledge bases are unimitable, socially complex and lead to exceptional performance (Grant, 1996). Therefore, the third and final hypothesis was developed as follows:

H_3: Cumulative Abnormal Return of acquirer in the short term following the announcement date will be higher for M&A transactions with higher cosine similarities.

5. Analysis and Results

Table 11. Group Statistics (Comparing cosine similarities within and across industries)

Sameind	N	Mean Cosine Similarity	Std. Deviation of Cosine Similarity	Std. Error Mean of Cosine Similarity
1	62	0.155	0.113	0.014
0	45	0.075	0.037	0.005

The variable Sameind =1 (Table 11) meant that the acquirer and target are in the same industry, whereas Sameind = 0 indicated that acquirer and target are in a different industry. In M&A transactions, the acquirer and target can be from various industries. For example, a firm involved in the business services industry or investment industry can acquire firms in the pharmaceutical or software industry. Such transactions are coded as 0. Cases, where the acquirer and firm were in the same industry, such as software or pharmaceutical or telecommunications, were coded as 1.

Table 12. Independent Sample T-Test (H_1: Comparing cosine similarities within and across industries).

t	df	Sig. (1-tailed)	Mean difference	Std. Error Difference	95% LCL	95% UCL
5.213	77.997	7.6E-7	0.080	0.015	0.049	0.111

The Levene's test for equal variances returned a P-value of 0, which indicated that the equal variance assumption was not met. The t-test results (Table 12) shows the t statistics and mean difference for situations where the equal variance assumption does not hold.

The independent samples test (Table 12) shows that the null hypothesis of equal means can be rejected. The mean cosine similarity will be higher for M&A transactions in the same industry, and the mean cosine similarity difference is 0.080.

The Mann-Whitney U test was also conducted to test the second hypothesis.

Table 13. Mann-Whitney U test Ranks (Comparing cosine similarities within and across industries)

Sameind	N	Mean Rank	Sum of Ranks
0	45	35.81	1611.50
1	62	67.2	4166.50

Table 14. Mann-Whitney U Test Statistics (H_1: Comparing cosine similarities within and across industries)

	Cosine
Mann-Whitney U	576.500
Z	-5.166
Asymp. Sig. (1-tailed)	1.2E-7

From the Mann-Whitney U test results (Table 14), the null hypothesis of equal mean ranks can be rejected.

To calculate the effect size of the Mann-Whitney U test, the following formula was used:

$\eta^2 = Z^2 / N-1$

$\eta^2 = (-5.166^2) / 106 = 0.2517$

Therefore, 25.17% of the variance in ranks is accounted for by the variable same industry.

For testing the third hypothesis, logistic regression was utilized.

In dyadic networks, such as M&A transactions where the acquirer and target form part of the dyad, there is a complication that the observations are not independent of each other, i.e. if firm D acquires E, and E acquires F, there are chances that D acquires F. Furthermore, the repeated observations could lead to a correlation between errors and erroneous calculation of standard errors. Despite this violation of independence, the logistic regression test was deemed to be the best test for the second hypothesis.

Table 15. Logistic Regression (H_2: Status of transaction vs. Cosine Similarity)

	B	S.E.	Wald	df	Sig.
Cosine	4.400	5.688	0.598	1	0.219 (1-tailed)
Empacqdiv	106035.500	125541.049	0.713	1	0.398
Emptargdiv	589289.491	228989.222	6.623	1	0.010
Constant	-1.180	1.334	0.782	1	0.377

For testing the third hypothesis, the dependent variable used was status, where 0 indicates that the M&A transaction was withdrawn and one suggests that the transaction was completed. The independent variables were cosine, empacqdiv, and emptargdiv. Both empacqdiv and emptargdiv were added in as control variables, as the M&A transactions are part of a dyadic pair.

From the logistic regression results (Table 15), no evidence was found to support the second hypothesis.

The social network software UCINET (Scott, Carrington, Borgatti, & Halgin, 2015) has a regression procedure that is robust to violations of independence. This regression model is a node-level network regression model that scrambles the dependent variables through many permutations. The scrambling of dataset results in many datasets with the dependent variable and the coefficients are compared with the sample distribution of coefficients from the random datasets that are permuted. The third hypothesis was tested using the node level regression model.

In UCINET, under tools, testing hypotheses, the node-level regression option was chosen. The regression method was selected as Y-perm (Y-Permutation) with the number of permutations and random seed set at 10000 and 32767, respectively.

The dependent variable was Carannpost, which is the CAR of acquirer one year post the announcement date. The independent variables added were cosine similarity along with empacqdiv and emptargdiv as control variables.

Table 16. Node-Level Regression Results (H_3: CAR of acquirer 1-year post-announcement date vs. Cosine Similarity).

Model	Coefficient	Unstandardized Std. Error	Standardized Coefficients (Beta)	t	Sig. (1-tailed)
Intercept	-0.431	0.111	0		
Cosine	3.223	0.663	0.459	4.864	0.000
Empacqdiv	0.457	0.490	0.087	0.932	0.102
Emptargiv	-4522.785	1662.797	-0.257	-2.720	0.000

From the network regression results (Table 16), we can conclude that cosine similarity has a highly significant effect on Carannpost after adjusting for the impact of empacqdiv and emptargdiv.

As cosine similarity is in the range of 0-1, the interpretation of Cosine variable slope would be: Ceteris paribus, a 0.1 increase in cosine similarity results in an increase of 0.322 (0.1*3.223) of Carannpost.

From the statistical analyses, there was evidence to support 2 of the three hypotheses. Finally, the squared term of cosine similarity was added to the linear regression model to investigate the functional form of the effect of cosine similarity on Carannpost. The node-level regression model in UCINET was chosen with the number of permutations and random seed set at 10000 and 32767 respectively.

Table 17. Node-Level Quadratic Regression Results (CAR of acquirer 1-year post-announcement date vs. Cosine Similarity Squared Term).

Model	Coefficient	Unstandardized Std. Error	Standardized Coefficients (Beta)	t	Sig. (1-tailed)
(Constant)	-0.010	0.164	0		
Cosine	-2.396	1.789	-0.341	-1.339	0.089
Cosinesq	10.925	3.259	0.851	3.352	0.004
Empacqdiv	0.595	0.465	0.114	1.280	0.065
Emptargiv	-3988.645	1577.957	-0.226	-2.528	0.001

Cosinesq is the squared term of Cosine Similarity. On adding the squared term of cosine similarity to the regression (Table 17), the linear term of cosine similarity was significant at the 10% level (Table 17), and the squared term of cosine similarity was highly significant and had a positive coefficient, which meant that as cosine similarity increases, the Carannpost increases at an increasing rate.

6. Conclusion & Limitations

I introduce the measure of cosine similarity as a measure of knowledge relatedness between acquirer and target in M&A transactions. From the logistic analysis, there was not enough evidence for cosine similarity to predict completion or withdrawal of an M&A transaction. However, as the independence assumption was violated, the logistic regression result should be viewed with caution. As cosine similarity had a highly positive significant effect on cumulative abnormal return one year post the announcement date, it would be beneficial for acquirers to acquire and merge with companies with higher knowledge relatedness, i.e., higher cosine similarities.

My paper answers the call of Arts et al. (2018) to use text matching to measure the similarity between patents. Future research can compare cosine similarities or other textual based similarity measures with USPTO classifications under an M&A setting. The Jaccard similarity and other text-based similarity measures can be incorporated into the analyses and compared with the results as obtained with the cosine similarity and USPTO classifications. Also, the dataset can be expanded to include more industries and control variables to take into consideration the effect of other factors that can impact stock performances of both acquirer and target. Specifically, variables such as R&D Expenditure/Sales (Absorptive Capacity) of the acquirer can be incorporated into the analyses to make the study more robust.

Since investors are more interested in the short-term gains of the acquirer, and the fact that the performance measure CAR provides more reliable results when used for short-horizon event studies, my study has been limited to using only CAR one year post the announcement date. CAR can also be extended to 2 years or 3 years to compute the long-term abnormal returns to compare with the results as obtained in this paper. Other market-related measures such as BHAR (Buy-and-hold abnormal return approach) which can be utilized for calculating long term abnormal returns can be explored, along with accounting measures such as ROA and ROE for measuring financial performance in M&A transactions.

Finally, sustainable competitive advantage in the long term for M&A transactions can be calculated using efficiencies in operations, knowledge transfers in R&D, and compared with the market based and accounting-based measures.

Final Chapter

General Conclusions

My first paper uses textual analytics techniques and Author Co-Citation analyses to explore the field of operations management over the past 21 years. The analyses show that as we move from the late ’90s to the late 2010s, the field of operations management has also evolved, incorporating the changes that take place in the research field around the world. Close inspection of the results reveals that specific topics such as manufacturing flexibility, strategic management, and psychology have remained influential throughout 21 years Newer topics such as healthcare operations management, information technology use in the supply chain. The pathfinder analysis on the selected author co-citation matrix revealed the four critical authors that are central to the field of operations management research over the past 21 years. The paper can be extended by adding more models such as a time lag model to explain the changes in topics over time, and a machine learning model that uses the topic-document probability matrix from LDA to predict which journal an article can get published into.

My second paper investigates the effect of social stress on individual inventory decision making. The participants are split into a control group that plays the standard newsvendor game and a treatment group that plays the standard newsvendor game with a social stress primal right before the newsvendor game. Analyses reveal that social stress improves learning and reduces demand chasing. The results encourage inventory managers to induce some social stress in the workplace. Further research can investigate the optimal point of social stress, as beyond a certain level of social stress one can realize diminishing returns. Another interesting treatment can be the interaction of time stress and social stress. This treatment would include the participant being subjected to the social stress treatment before playing the newsvendor game and then being given limited time for entering the order quantity while playing the newsvendor game. Operations management games that add an upstream supplier or downstream retailer such as the beer game can also be used in a social stress setting. Future studies could use brain-scanning techniques such as functional MRI (fMRI) to visualize and understand the inner workings of the brain when participants are subjected to different stress treatments in an OM setting.

My third chapter uses the field of Mergers & Acquisitions to examine the effect of knowledge relatedness between the acquirer and target on the status of a transaction (Completed or Withdrawn), and whether knowledge relatedness can impact the post-financial performance of the acquirer in the short term. The event study in M&A was used to determine the financial performance measure, Cumulative Abnormal Return (CAR). I use knowledge flows between the acquirer and target as visualized in the patent text data from both acquirer and target to measure the technological similarity between them. Specifically, I utilize the cosine similarity measure as a measure for knowledge relatedness, rather than relying on traditional USPTO classifications to incorporate the actual patent content on acquirer and target. My use of cosine similarity as a measure of knowledge relatedness is justified since technological similarity can be utilized as a proxy for knowledge relatedness. Subsequent analyses revealed that while cosine similarity was not useful in predicting the M&A transaction being withdrawn or completed, acquirers with higher cosine similarities had significantly higher post-performance CAR in the short term. Future studies can investigate the effects of other text-based similarity measures on the post-M&A performance of acquirer, use more control variables, and experiment with different financial performance measures based on stock market performance such as BHAR along with accounting measures such as ROA or ROE.

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Appendix A (Stress Overload Scale):

Read each item and then mark the appropriate answer in the space next to that word**. Indicate to what extent you feel this way right now, that is, at the present moment**

1	**2**	**3**	**4**	**5**
very slightly or not at all	a little	moderately	quite a bit	extremely

After this experiment, do you feel:

- Strained? _____
- Overextended? _____
- Swamped by your responsibilities? _____
- That there wasn't enough time to get to everything? _____
- Like you were rushed? _____
- Like you had a lot on your mind? _____
- Like things kept piling up? _____
- Like you had to make quick decisions? _____
- Like you didn't have time to breathe? _____
- Like you were carrying a heavy load? _____
- Like there was "too much to do, too little time"? _____

Appendix B (Cognitive Reflection Test):

Please answer the following questions:

1. A bat and a ball cost $1.10 in total. The bat costs $1 more than the ball. How much does the ball cost?

2. If it takes five machines five minutes to make five widgets, how long does it take 100 machines to make 100 widgets?

3. In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake?