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Review

A journey from normative to behavioral operations in supply chain management: A review using Latent Semantic Analysis

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ABSTRACT

This study aims to systematically review the cross disciplinary literature covering the time period from 1934 to January 2013 on behavioral operations in supply chain in order to identify and define the taxonomy of the research on power influences in supply chain. A list of noted journals and search results from Science Direct and Web of Knowledge, IEEE Xplore, and INFORMS (approximately 11,000 journal articles) is used to prepare content collection. Latent Semantic Analysis (LSA) is applied as the review and knowledge extraction methodology. Using the text analysis and mining method we can combine statistical methods and expert human judgment to extract knowledge in the form of key latent factors. The LSA based analysis gives the study a scientific grounding which helps to overcome the subjectivity of collective opinion about the trends. This approach allows proposing taxonomy of the research on power influences in supply chain. The adopted systems approach is used to find research gaps in each class of taxonomy. An emerging trend is noticed in the research of behavioral operations in supply chain. Understanding such a scholarly structure and future trends will assist researchers to assimilate the divergent developments of this multidisciplinary research in one place. This review will be beneficial for practitioners as they consider behavioral aspects in decision making. We have also studied articles related to supply chain published in Expert Systems with Applications (ESWA) journal. We have speculated what an ESWA-related community would like to see in future publications. This will encourage researchers to explore the recommended areas and publish to these outlets.

1. Introduction

The term "supply chain management" was first coined by a Booz Allen consultant, Keith Oliver, in 1982. Supply Chain Management (SCM) has been theorized over the last 30 years. Different relational approaches for interorganizational interplay, namely cooperation, coordination, and collaboration have been taken up to enhance the performance of a Supply Chain (SC) (Albino, Dangelico, & Pontrandolfo, 2012; Atanasova & Senn, 2011; Caro & Gallien, 2012; Faraj, Jarvenpaa, & Majchrzak, 2011; Kim, Ha, Lee, Jo, & El-Saddik, 2011; Kim & Netessine, 2013; Klassen & Vereecke, 2012; Kravari, Bassiliades, & Boley, 2012; Lavie & Drori, 2012; Liu & Zhang, 2013; Lozano, Moreno, Adenso-Díaz, & Algaba, 2013; Nyaga, Whipple, & Lynch, 2010; Peng, Heim, & Mallick, 2012; Pietrobelli & Rabellotti, 2011; Pimentel Claro & Oliveira Claro, 2010; Rodríguez Monroy & Vilana Arto, 2010; Smirnova, Henneberg, Ashnai, Naudé, & Mouzas, 2011; Tang, 2010; Topolsek, Cizman, & Lipicnik, 2010; Verma, Mishra, & Sinha, 2011; Wu, Loch, & Ahmad, 2011; Xia, Xiao, & Zhang, 2013; Yoon & Nof, 2010; Yu & Nagurney, 2013; Zhang & Chen, 2013; Zhang, Gou, Liang, & Huang, 2013). An extensive literature review of what happened in this domain has been covered in this research. The review reveals that despite a lack of interest in the initial phase, the study of behavioral operation in supply chain is growing. Hence, a state-of-the-art review has been attempted to show the multidimensional growth of research interest in this particular field on a single platform.

This review covers the years from 1934 to January, 2013. Our review aims to cover the research database from the major areas: Operations Research, Operations Management; Engineering; Business Economics; Computer Science. The published research articles in journals available on the Web of Knowledge database, Science Direct, IEEE Xplore, and INFORMS are used as primary data sources

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in this study. The title and abstract of research articles are processed using data mining techniques. We use Latent Semantic Analysis to study abstracts of all selected articles and propose taxonomy of the research on power influences in SC. A systems approach is adopted to find research gaps in each class of taxonomy. Comprehending such a scholarly structure and future trends will help supply chain researchers assimilate the scattered developments of this multidisciplinary research in one place. This will also be useful for academia in projecting research directions, planning for special issues in journals, and setting up themes for conferences in this field. This review will be useful for supply chain practitioners to consider behavioral aspects in decision making. Furthermore, the LSA based analysis gives the study a scientific base which helps to overcome the subjectivity of collective opinion regarding the trends. We also predict the kinds of applications of expert systems expected for future research in supply chain domain. This will help researchers to find outlets for their research articles prepared to publish in Expert Systems with Applications (ESWA) Journal.

This study aims to review the cross disciplinary literature on behavioral operations in supply chain. The major significance of this study is summarized as follows:

1. One of the motivations of this review was to conceptualize the evolution of research topics in supply chain. We have tried to cover a wide span of time, as past as there was an article on supply chain in literature. This review paper covers almost eight decades, from 1934 to January 2013. This allowed us to visualize the evolution of research topics over this period.
2. Finding emerging trends has always been a key contribution of any review work. We have speculated on emerging topics for supply chain, as well as possible research on the application of expert systems in supply chain domain. We have proposed possible outlet for research on supply chain by ESWA community researchers.
3. This study presents a scholarly structure and future trends to assimilate the divergent developments of this multidisciplinary research in one place. We have proposed a taxonomy for behavioral theoretical architecture of supply chain management.

The discussion is divided into four sections. Section 2 is an introductory discussion on LSA to get familiar with the method. Section 3 is on data collection and analysis. Results of this research are discussed in Section 4. In addition, we present potential future research directions in behavioral operations in supply chain in Section 4. Finally, major contributions from this study are summarized as conclusions in Section 5.

2. An introductory discussion on Latent Semantic Analysis

Latent Semantic Analysis was introduced in late 1980s (Deerwester, Dumais, Furnas, Landauer, & Harshman, 1990) which means it is concurrent with the supply chain management concept. In the beginning phase it was used to improve information retrieval systems for library indexing and search engine query performance (Cios, Pedrycz, Swiniarski, & KurganL, 2007; Dumais, 2004, 2007; Han & Kamber, 2006; Manning, Raghavan, & Schütze, 2009). Gradually this technique was adopted by psychology researchers (Landauer, 2007) and it has been deployed in the research of artificial intelligence, cognitive sciences, education, and information systems.

The basic idea of LSA is to extract hidden knowledge from a set of texts. It processes text (a "document") from a set of files (a "corpus") and identifies keywords (a "term"). Further, it helps to find latent factors (a "topic") from these extracted terms. The mathematical foundation of LSA is built by (Martin & Berry, 2007). Valle-Lisboa and Mizraji (2007) discussed how LSA discovers latent words (terms) with an analogy of the working principle of the

Table 2
Reduced term frequency matrix (6×6).

	DOC1	DOC2	DOC3	DOC4	DOC5	DOC6
commun	1	0	0	0	1	0
effect	1	0	0	0	1	0
social	0	1	1	0	1	0
explor	0	1	0	1	0	0
inform	0	1	0	0	1	1
predict	0	0	0	0	2	0

Table 3
Transformed term frequencies after TF–IDF generation.

commun	1.584963	0	0	0	1	0
effect	1.584963	0	0	0	1	0
social	0	1.584963	1	0	1	0
explor	0	1.584963	0	1.584963	0	0
inform	0	1.584963	0	0	1	2.584963
predict	0	0	0	0	2	0

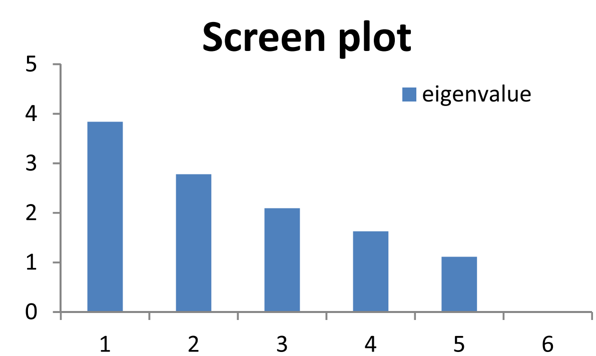

Fig. 1. Screen plot (*x*-axis: Latent factors, *y*-axis: Eigen values).

Table 1
Selected documents to demonstrate LSA as text mining tool.

Document ID	Title	Decision Support Systems Journal, volume 55, issue 4, page reference
DOC1	Digital health ***communities***: The ***effect*** of their motivation mechanisms	941–947
DOC2	Privacy preserving actions of older adults on ***social*** media: Exploring the behavior of opting out of ***information*** sharing	948–956
DOC3	A **social** network empowered research analytics framework for project selection	957–968
DOC4	Distance matters: Exploring proximity and homophily in virtual world networks	969–977
DOC5	**Social** network embedded ***prediction*** markets: The effects of ***information*** acquisition and ***communication*** on ***predictions***	978–987
DOC6	**Information** and trust in hierarchies	988–999

Table 4
Term loading with two latent factors.

Term	Before varimax rotation		After varimax rotation	
	Factor 1	Factor 2	Factor 1	Factor 2
commun	0.228184	−0.55337	0.875872	−1.53912
effect	0.228184	−0.55337	0.875872	−1.53912
social	0.427868	0.051689	1.64235	0.143765
explor	0.299525	0.35391	1.14971	0.984353
inform	0.729815	0.330351	2.801355	0.918826
predict	0.300746	−0.38796	1.154395	−1.07905

Table 5
Document loading with two latent factors.

Document	Before varimax rotation		After varimax rotation	
	Factor 1	Factor 2	Factor 1	Factor 2
DOC1	0.188442	−0.63068	0.723326	−1.75414
DOC2	0.601707	0.419382	2.30962	1.166453
DOC3	0.111469	0.018584	0.427868	0.051689
DOC4	0.123679	0.201676	0.474736	0.560935
DOC5	0.577198	−0.53952	2.215542	−1.50061
DOC6	0.491486	0.307024	1.886544	0.853945

human mind. A review of issues and solution techniques of various challenges in LSA is done by Evangelopoulos, Zhang, and Prybutok (2012).

LSA starts with a Vector Space Model (VSM) (Salton, 1975). In this method, a corpus with d number of documents compiles (stemmed using term stemming algorithm (Porter, 1980) and a vocabulary of t number of terms is generated. We remove common words from this list of terms using a stop list of words like “the”, “of”, etc. The next step is to generate a ($t \times d$) matrix TF. An element of TF matrix (f_{ij}) is the frequency of occurrence of the term (ith) in jth document. This matrix is known as term-frequency

Table 6
Number of articles included in this study.

Year	Number of articles	Number of articles from ESWA related to supply chain
1934–1949	1	
1950–1959	25	
1960–1969	199	
1970–1979	290	
1980–1989	330	
1990–1999	1169	4
2000–2009	5456	262
2010–2013	3675	481
2014 onwards		102

matrix. This TF matrix is multiplied by the inverse document matrix to normalize the frequencies. This resultant matrix is known as TF–IDF matrix. Each element of TF–IDF can be generated using Eq. (1).

$$a_{ij} = f_{ij} \cdot \log_2(N/n_i) \tag{1}$$

where, N is the total number of documents in the collection and n_i is the frequency of term i in the entire collection of documents.

A Singular Value Decomposition (SVD) operation is done on the resulting TF–IDF matrix. It decomposes the TF–IDF matrix into three matrices – U, S, V; where U = the term eigenvectors; V = the document eigenvectors; S = a diagonal matrix of singular values (i.e., square roots of common eigenvalues between terms and documents in the least squares manner). The SVD of TF–IDF dimensionality is truncated by keeping the first k dimensions to avoid over-fitting of factors.

The next step is to find out term load and document load for each factor. By this step we can cluster terms clearly with a particular factor and the same for the document. The varimax method is widely used for this purpose. It is capable of simplifying the term loadings by making them either very large or very small such that

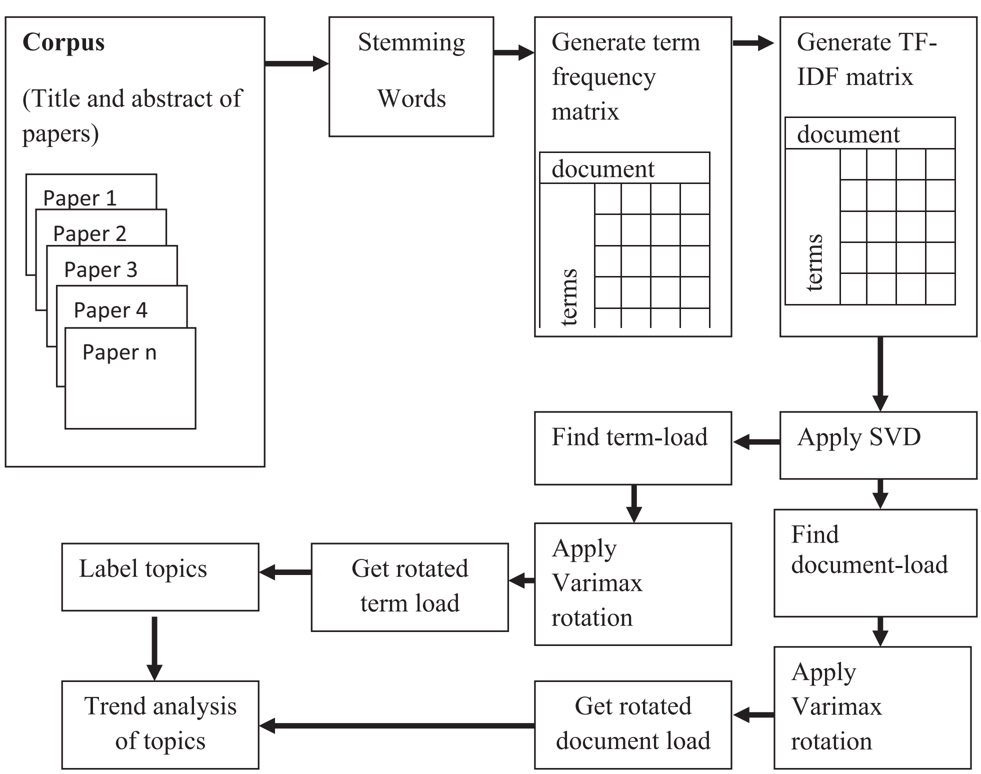

Fig. 2. Flowchart of the data collection and analysis.

Table 7
Topics (Latent factors).

	Topic	Method
1.1	Factor 0: System model for behavioral operation decision problem	Time based probabilistic model
1.2	Factor 1: Product competition in business	Game theory, hypothetical experiment
1.3	Factor 2: Relational aspect in management techniques	Scientific approach, logics based on economics
1.4	Factor 3: Service system design	Queuing theory
1.5	Factor 4: Object oriented design	
1.6	Factor 5: Human behavior analysis on decision making	Computer based approach
1.7	Factor 6: Algorithm design for traveling salesman problem	Branch and bound, integer programming, cutting-plane, graph theory
1.8	Factor 7: Information security	
1.9	Factor 8: Service supply chain management	Academic research, technology driven analysis
1.10	Factor 9: Market research	
2.1	Factor 0: Modeling production and supply chain systems for performance improvement	Developing framework, theory, performance measure
2.2	Factor 2: Single period discounting policy design for overstock in inventory	
2.3	Factor 3: Firm's economy	Game theory
2.4	Factor 4: Product pricing and behavior analysis of marketing channel in an oligopolistic market	
2.5	Factor 5: Supply chain decision making in oligopolistic market	
2.6	Factor 7: Development of metaheuristics for vehicle routing, lot sizing, and facility location–allocation problem	Integer programming, combinatorial optimization, neighborhood search, tabu search, mixed integer programming, multi-objective optimization, probabilistic model, simulated annealing, Lagrangian method, branch and price, branch and bound, hill-climbing, nondominated solution search, bacterial algorithm, linear programming, risk-based algorithm, relaxation-based algorithm
2.7	Factor 8: Supplier–buyer relation (supplier selection, risk management)	
2.8	Factor 9: Shareholding between partners	
2.9	Factor 10: Information sharing	Game theory
2.10	Factor 11: Component assembly	
3.1	Factor 0: Optimization model for operations management and supply chain	Stochastic model, algorithm design, heuristics, game theory, Markov process, mixed integer programming, convex and nonconvex optimization, news vender problem, simulation based solution, meta-model
3.2	Factor 2: Vehicle routing, lot sizing, multiple order, multiretailer, facility location	Solution of constrained optimization, branch and bound, neighborhood search, near optimum, expectation maximization, problem specific solution
3.3	Factor 3: Inter-organization relations (mediated and nonmediated)	Empirical study, survey, hypothesis testing
3.4	Factor 4: Product pricing and behavior analysis of marketing channel in an oligopolistic market	
3.5	Factor 5: Supply chain decision making in oligopolistic market	
3.6	Factor 6: Prediction model development	Petri net, UML
3.7	Factor 7: Order management	
3.8	Factor 8: Revenue sharing model	Game theory
3.9	Factor 9: Service operation	
3.10	Factor 10: Supplier–buyer relation	

the rotated factor space can be easily interpreted. High loading terms are generated from the rotated term loadings U_kS_k and high loading documents generated from the rotated document loadings V_kS_k. These matrices help to correlate latent terms to a particular factor (topic).

We illustrate the text mining by LSA using a very small set of textual data shown in Table 1. The documents are titles of six selected articles published in *Decision Support Systems Journal, volume 55, issue 4, pages 861–1000 (November 2013)*. The steps followed here are the same as we have used in our main study. We start with the text preprocessing in which 37 words filtered out from a total of 64 words by excluding trivial English words such as "and" or "of" using a *stoplist*. This step also includes the term stemming in which terms get replaced by their stem word or set of characters (e.g., "communities" get consolidated as "commun-", "information" get consolidated as "inform-"). We also exclude terms that appear only once in the total document collection, such as "capacities" or "procurement". The final vocabulary after text preprocessing is reduced to six stemmed terms. The final vocabulary for this example is (commun-, effect, social, explor-, inform-, predict). The occurrence of original words related to these terms is italicized and made boldface in Table 1. Table 2 shows the reduced term frequencies for each of the six documents, organized in a 6×6 term-by-document matrix. Table 3 shows the term frequency matrix after a transformation based on Inverse Document Frequencies (TF–IDF) to penalize frequent terms and promotes rare terms in documents. Next, a Singular Value Decomposition (SVD) operation is done on TF–IDF matrix (on data presented in Table 3).

Fig. 1 shows a screen plot of the six eigen values (3.84, 2.78, 2.09, 1.63, 1.11, 7.88×10^{-17}) generated by LSA. Based on this plot k number of factors have to be taken for next analysis. Several methods exist to select a value for k. Likewise in our original study here we are taking top n number of factors. Here we have taken top two factors.

The next steps will help to interpret the meaning of these latent factors. A varimax rotation is used to magnify association of a term with a latent factor. Table 4 shows the term loadings before and after a varimax rotation where Factor1 appears to be mostly related to all terms after rotation. Similarly, we can prepare the document loading (presented in Table 5).

Factor1 loads high on all documents. After examining these term load and document load matrices we can build the statistical patterns for the first two latent factors. Our LSA model suggests that these documents are talking about *exploring social information to predict effects*. The construction of labels for factor also is an important task (here Factor1 has been labeled as *exploring social*

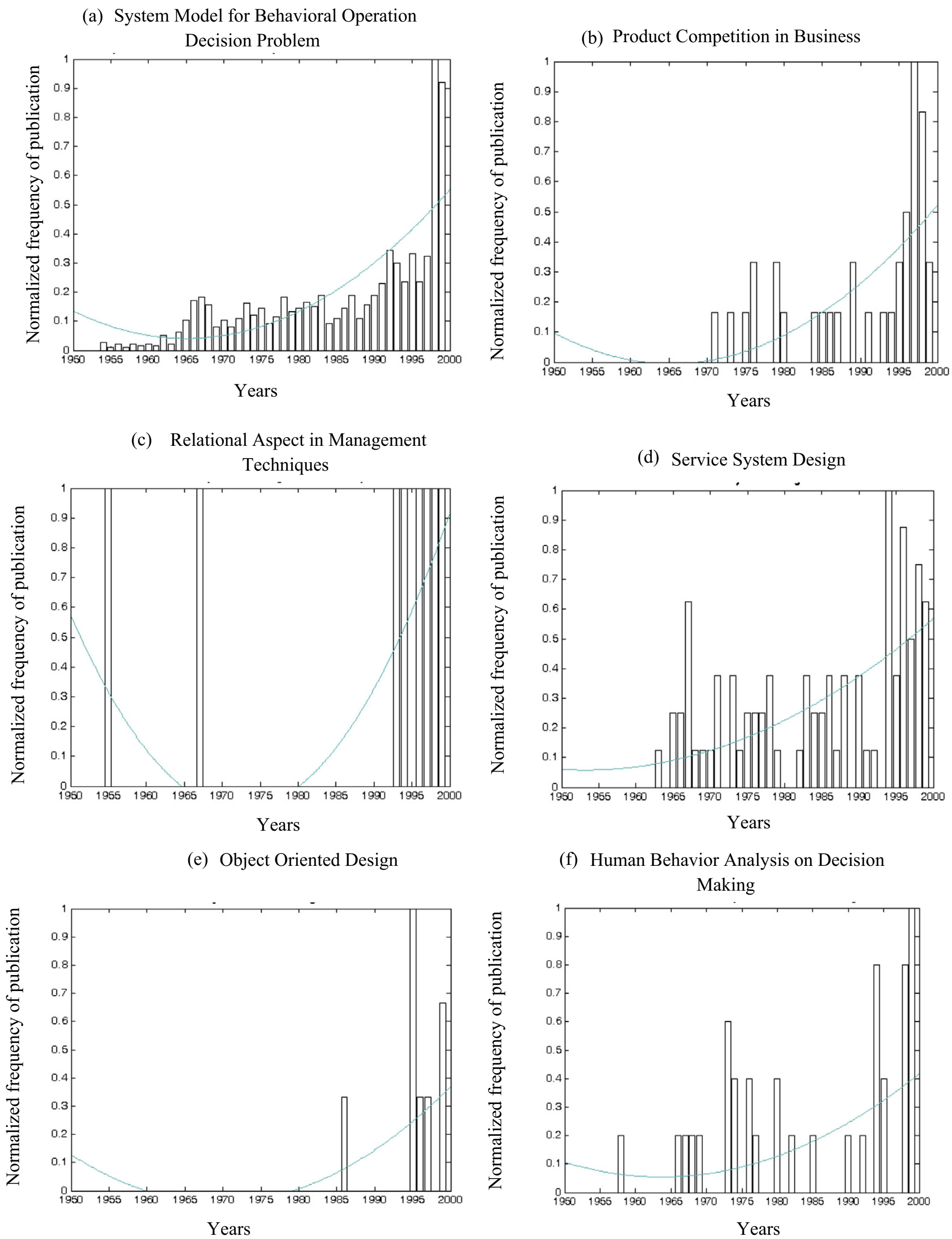

Fig. 3. Trend analysis of topic for the period 1934 to 1999 (part 1).

information to predict effects). In our original study we have used Nominal Group Technique (NGT).

The strengths of LSA have influenced us to select it over any other analytical methods such as Principal Component Analysis (PCA), which could be used to accomplish the same. LSA provides a good approximation related to several aspects of human language learning and understanding. Specifically, where text alone does not explain the context of a word, LSA works as good as human with 90% accuracy. It is also found that LSA might be only about 10% inferior to humans understanding the order of the words to extract information (Landauer & Dumais, 2008). This technique has been argued as fundamentally wrong as it is not linked with concept of perception and intention behind using a word. But this argument has also been clarified with the fundamental concepts of a language (Landauer & Dumais, 2008).

3. Data collection and analysis

We have used Latent Semantic Analysis on a corpus that is representative of supply chain management research. The flowchart is in Fig. 2. In the first step terms are identified and stemmed to remove suffixes from the terms. Then, a term frequency matrix is generated. In this step we exclude the terms having only one appearance in the whole document set in the corpus. In the next step, we prepare term frequency–inverse document frequency (TF–IDF) matrix is generated. The singular value decomposition and factor rotation (Varimax rotation) method is applied on TF–IDF matrix. Final term loadings and document loadings are done on a rotated matrix. Everything up to this point is done using a java program. We get results in comma separated value (CSV) file format and use them for further analysis (factor naming). Finally,

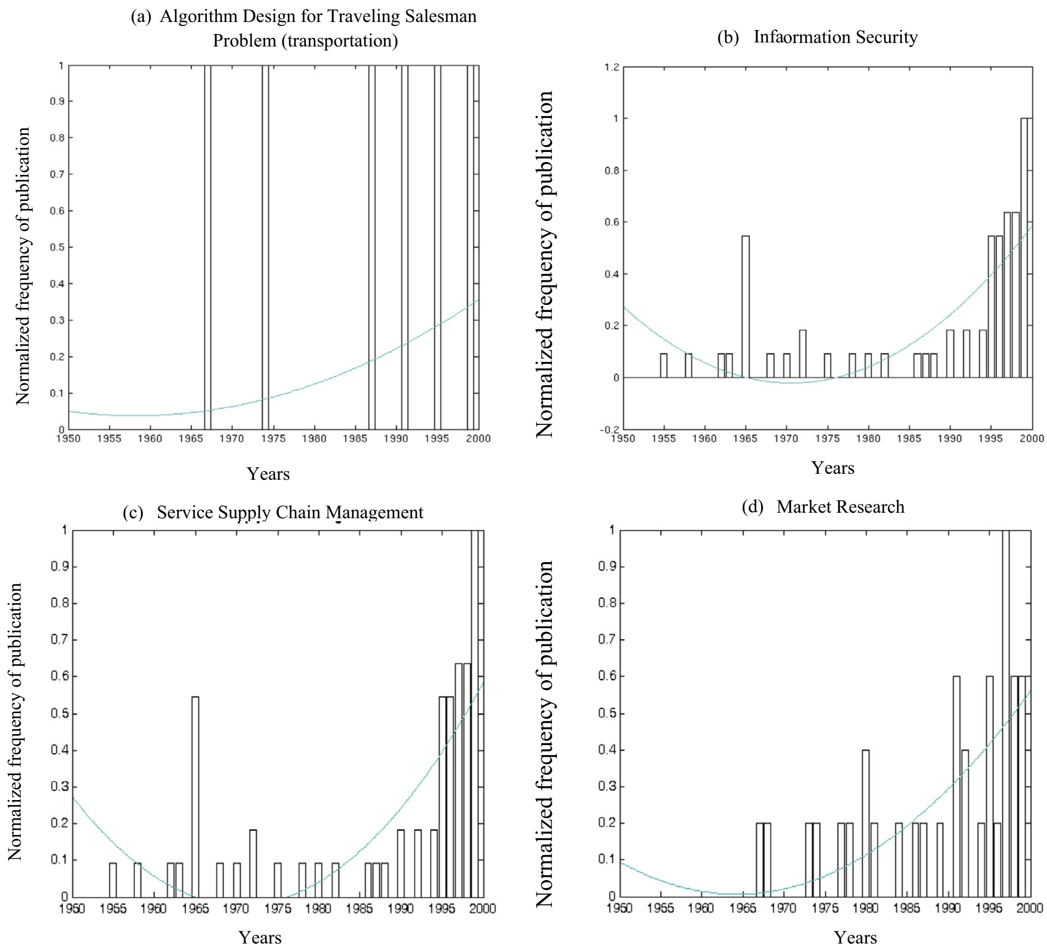

Fig. 4. Trend analysis of topic for the period 1934 to 1999 (part 2).

the plots showing research publication trends over time are developed for different factors based on a highly loaded document derived from Factor analysis. This section includes discussion on data collection and the various analysis steps.

3.1. Data collection

We started collecting data with the preparation of a list of appropriate journals which cover the domain identified in keywords. It starts with well known journals for publishing high quality research in supply chain and operation management. We include established journals like Management Science (MS) and Journal of Operations Management (JOM), affiliation with professional societies (Production and Operations Management Society for POM journal, Institute for Operations Research and Management Sciences for MS and MSOM, American Production and Inventory Control Society for JOM). The list includes reputed journals like Manufacturing & Service Operations Management (M&SOM), Decision Science Journal, Organization Science, Operations Research, INFORMS Journal On Computing, Management Science, IIE Transactions, IEEE Transactions on Engineering Management, SCM: An International Journal, Production and Operations Management (POM), Journal of Operations Management (JOM), International Journal of Services and Operations Management (IJSOM), Computers & Operations Research, MIS QUARTERLY, Journal of Business Logistics, Computers & Industrial Engineering, International Journal of Physical Distribution & Logistics Management, New Left Review, Journal of the Operational Research Society, Omega, International Journal of Production Economics, European Journal of Operational Research (EJOR), Industrial Marketing Management, Expert Systems with Applications, Decision Support Systems, The Lancet, World Development, British Food Journal, Industrial Management & Data Systems (IMDS), International Journal of Production Research (IJPR), Naval Research Logistics, Transportation Research Part E, Logistics and Transportation Review, Agrekon, Agricultural Economics, Clean Technologies and Environmental Policy, Electronic Commerce Research and Applications, International Journal of Advanced Manufacturing Technology, Journal of Organizational Computing and Electronic Commerce, Telecommunications Policy, Advances in Engineering Software, American Journal of Agricultural Economics, Chemical Week, Computers & Chemical Engineering, Energy, Energy Policy, Food Policy, Information Systems Management, International Food and Agribusiness Management Review, International Journal of Electronic Commerce, International Transactions in Operational Research, Internet Research, Journal of Agricultural Economics, Journal of Cleaner Production, Journal of Computer Information Systems, Journal of Strategic Information Systems, Proceedings of the Institution of Mechanical Engineers Part D, Journal of Automobile Engineering, and Production Planning and Control.

Titles and abstracts of research papers are taken from the electronic library such as Web of Knowledge, Science Direct, IEEE Xplore, INFORMS. We have considered only journal articles, conference proceedings, book chapters (title only) in this study. Specifically, we have used “behavior”, “behavior” and “supply chain” as search keywords. In the present literature, “behavioral operations”

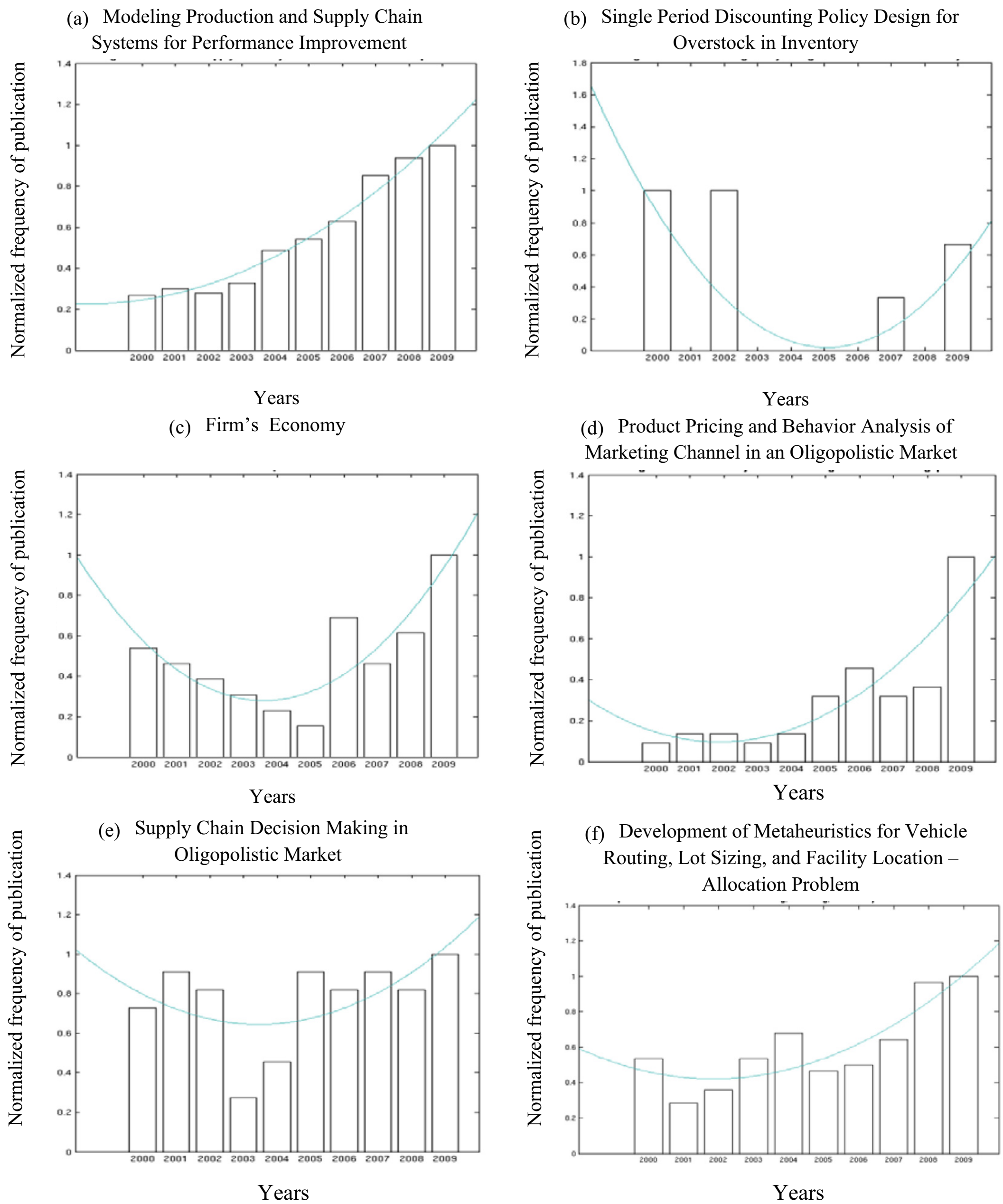

Fig. 5. Trend analysis of topic for the period 2000 to 2009 (part 1).

means research that explores the interaction of human behaviors and operational systems and processes. Specifically, behavioral operation is interested in identifying ways in which deviations from rational behaviors impact operational performance differently (for better or for worse). This area requires knowledge outside of formal operation management like cognitive psychology, social psychology, group dynamics, and system dynamics (Bendoly, Croson, Goncalves, & Schultz, 2010). The literature reviewed in this paper covers a wide horizon of supply chain. Our motive is to present the journey from normative to behavioral issues researched in Supply Chain Management, rather than confined only to the behavioral aspect of operations in supply chains.

The search period was not restricted, but the results were drawn from the time span of 80 years (from 1934 to 2013). There were 11,145 documents found relevant and shortlisted for further analysis. There are a few interdisciplinary articles in these shortlisted documents. Table 6 lists the number of articles included in our study by decade. It also contains a number of articles published on supply chain in ESWA Journal. This corpus has been used in predicting future research in ESWA and is detailed in Section 4.4.1.

3.2. Preparation of corpus

The number of articles published in 2010–2013, 2000–2009 is quite high compared with other decades. We break collected documents into three sets. First set (set1) consists of documents from 2010–2013. Second set (set2) consists of documents from 2000–2009. Third set (set3) includes the remainder of the documents (1934–1999). Each set is considered as a separate corpus.

3.3. Generation of the term frequency matrix

The following steps have been done for each corpus –set1, set2 and set3. Filtering terms (words) by applying a custom stop list,

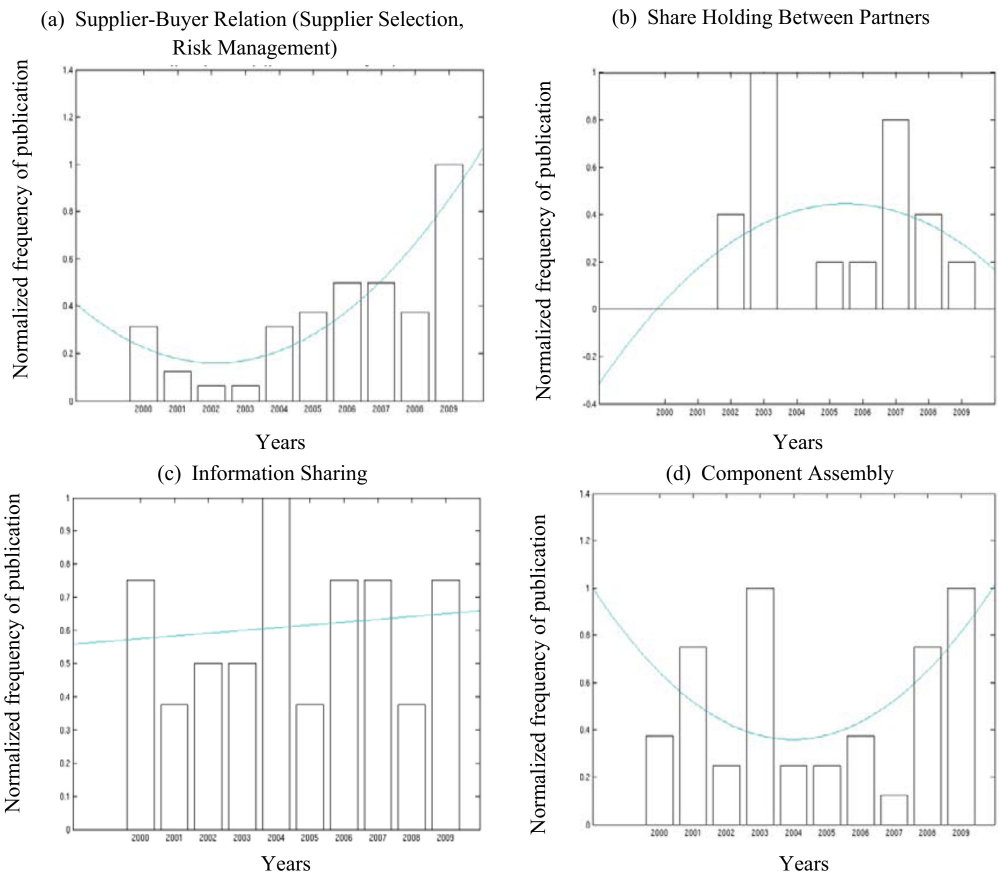

Fig. 6. Trend analysis of topic for the period 2000 to 2009 (part 2).

based on the original 571 stop words of the SMART system (available for download from ftp://ftp.cs.cornell.edu/pub/smart/english.-stop) is a common practice in text mining. We added "abstract" and "title" to that list to filter out these words. Term stemming is done and terms with a single occurrence in the corpus were excluded. This step produced a vocabulary of stemmed terms. Term frequency matrix is transformed to term frequency–inverse document frequency (TF–IDF) matrix to compress the frequencies (Robertson, 2004; Salton, 1975; Sidorova, Evangelopoulos, Valacich, & Ramakrishnan, 2008; Wei, Hu, Tai, Huang, & Yang, 2008). This is achieved by multiplying the Term Frequency (TF) by the Inverse Document Frequency (IDF). Generalized expression for each element of TF–IDF matrix is

$$w_{ij} = \mathrm{TF}_{ij} \cdot \mathrm{IDF}_i = \mathrm{TF}_{ij} \cdot \log_2(N/n_i) \qquad (2)$$

where, N is the total number of documents in the collection and n_i is the frequency of term i in the entire collection of documents.

3.4. Extraction and labeling of the Latent Semantic factors

A Singular Value Decomposition (SVD) operation is applied on TF–IDF matrix to get latent factors. We have implemented this process using Java code based on NIST's JavaNumerics JAMA package (available for download from http://math.nist.gov/javanumerics/). LSA allows the user to choose a few latent factors and do further analysis on "k" selected factors (Bradford, 2008; Efron, 2005; Zhu & Ghodsi, 2006). We are taking the top ten factors (having top ten Eigen values in SVD matrix) for the next step. We generate term load and document load matrix (using varimax method) to find the best correlation of a term (or document in document load) with a latent factor. Results for three different corpus sets are presented in the next section. Factor labeling is achieved with the help of expert opinion (based on term load values). While preparing the corpus, we have used a 'year-documentID' (such as 2011-xxxxxx) format to create document file names. It is useful to utilize document-load to find a time trend of research direction. The next section is on such trends analysis in SCM research.

4. Results and discussion

The result is presented systematically in the form of graphs and is tabulated to enhance readability of the report. First, we will present the outcome of LSA, identified as the top ten topics (or latent factors) in an assembled format over approximately eight decades. Next is the disassembled representation of the trends in topics of SCM research. The interesting observations present in this study are a projection of a scholarly system view of SCM.

4.1. Identified latent topics and their analysis over eight decades

The comprehensive process of identifying latent factors is the prime focus of this subsection. The discussion is oriented towards a scholarly analysis of domain knowledge of SCM. We start with the assembled results of three sets of corpora. Based on screen plot and expert opinion we come up with 30 topics (latent factors). We represent these 30 factors as "core topics" in this knowledge domain. This core is not confined to behavioral operations but includes milestones across the journey from normative to behavioral supply chain. Within the factors beyond "core topics" are found more specialized subdomains. Incorporation of those factors reduces the generic view of the analysis.

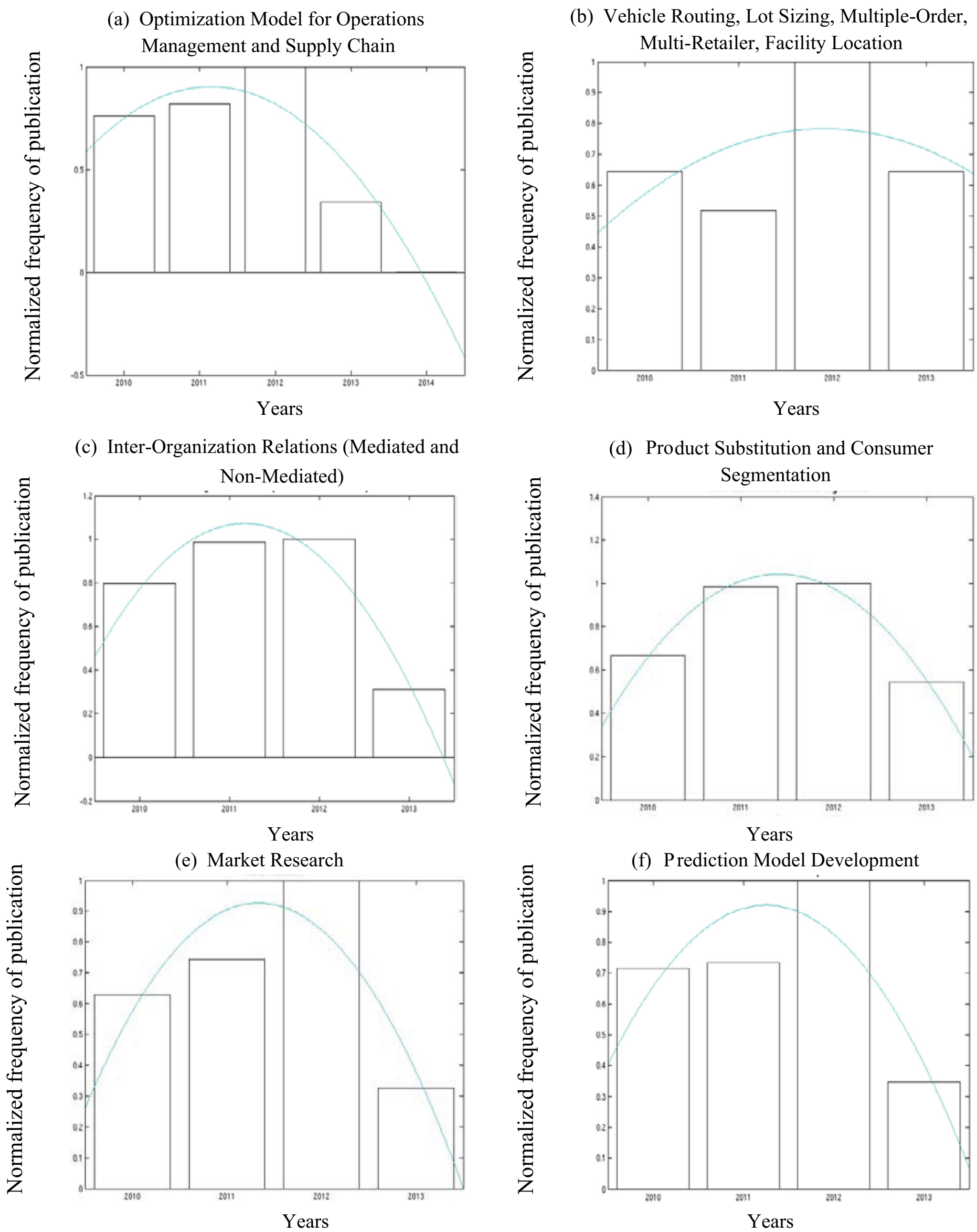

Fig. 7. Trend analysis of topic for the period 2010 to 2013 (part 1).

Naming latent factors suffers from the fact that they are highly subjective. We have followed NGT to compile expert opinion for naming latent factors (Delp, Thesen, Motiwalla, & Seshardi, 1977). We have consulted four senior researchers of supply chain domain. Two of them are editorial board members of reputed journals of supply chain, operation management and decision sciences. They are geographically located in U.S., U.A.E. and India. We have used web based interaction through *Skype* to conduct this event. The results in form of topic name for each topic have been ranked and selected through voting. The redundant solutions have been discarded and conflicts have been resolved through online discussion.

Table 7 presents the top 30 topics and methods used in solving problems in their respective domains. Figs. 3–8 depict topic trends over the past eight decades. The results presented are useful to a supply chain researcher who has just started venturing into this field and is looking for a holistic view. The key assumptions we have taken are that an abstract and title of a published piece of literature are a manifestation of the full content and thus provides a comprehensive view about the topic discussed in the particular paper. The results reported in graphs present a development in knowledge from outside the formal training for an intrepid researcher to venture into new terrain.

The top ten factors from each of the three different clusters are considered in order to analyze SCM topics. A few expected observations include the decline of research areas which were prime foci in the early decades. "Product differentiation" is one of the early methods to get competitive advantage in the market. Service, after sale, became important for customer satisfaction. We observe a gradual growth in service system design which began 50 years ago. At the same time, analysis of human behavior for decision making begins with system dynamics. Market research and service operation study is always in the top ten directly or in forms like marketing channel, product pricing problem, and service supply

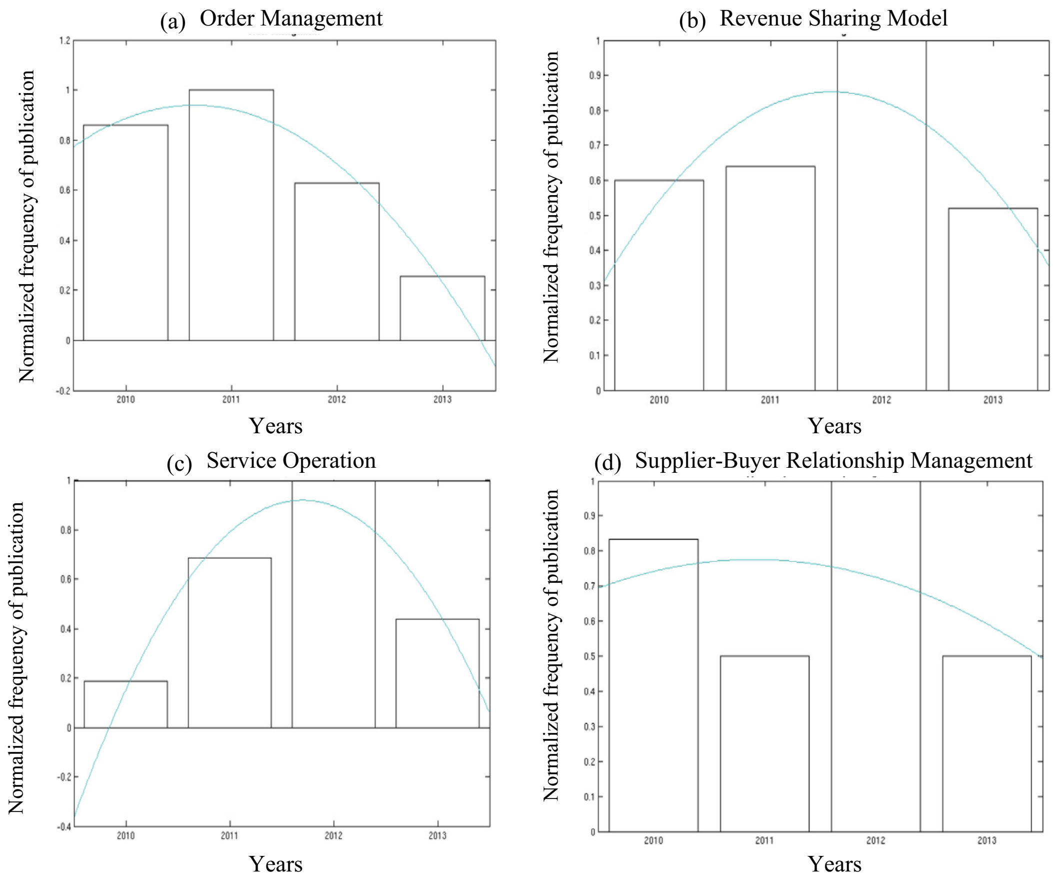

Fig. 8. Trend analysis of topic for the period 2010 to 2013 (part 2).

chain. The study of a firm's economy was in focus during early 2000. In the pre-internet era information security was not much discussed, but was still a consideration. Introduction of the internet and ERP system raise a new issue – information sharing policy between supply chain players.

The behavioral aspects in system design evolved along with the conceptualization of supply chain. It has transformed from a relational model for decision making towards a more specifically supplier buyer relation (supplier selection and risk management); thereafter to a behavioral model for revenue sharing although it began as shareholding between partners, and order management.

Important recurring trends are found particularly in system models for behavioral operation decision and in human behavior analysis on decision making. The change in technology influences changes in manufacturing techniques. Similarly, human reaction towards this shift in techniques triggers the birth of new technologies; perhaps, this phenomenon produces a cyclic change in the organizational and socio-technical impact analysis and behavioral model with quantum advancement of technology.

Another interesting spiral trend is found in the area of supply chain involving Vehicle routing, lot sizing, multiple order, multi-retailer supply chain, facility location problem in multi-echelon systems. In the early decades, an area known as the traveling salesman problem, discounting and Lot sizing, Inventory Planning, and object oriented design approach was written about at firm level. An important reason for this decline is the advent of RFID, use of artificial intelligence and metaheuristic algorithms in practice. The introduction of the internet has changed the market. Availability of information (through MRP, ERP) reduced the communication gap between supply chain players and improved the visibility throughout the chain. As a result, an uncertain characteristic of supply and demand becomes more predictable. But, the problem is elevated from firm level to a higher level i.e., that of end-to-end supplies chain. The solution techniques for the Traveling Salesman Problem is now applicable for developing a routing policy of automated guided vehicle (AGV) and other automated systems. Another case is product differentiation. In the early decades, 30 years ago, companies tried to achieve a competitive advantage from that. At present, companies are trying to segment customers rather than products. The research focus has shifted from system models to performance measures of the models. Consequently, optimization model development for every operation is getting more attention at present.

4.2. Discussion on identified research methodologies associated with latent topics

The analysis of documents for topic is analogous to analysis for research method. While labeling factors for topic name, we find stemmed terms (like hypothesi_, Metaheuristic_, opti_, markov, simul_, etc. where a suffix like 's', 'es', 'tion', 'ing' are removed during stemming the word) that are mostly describing research methodology. We arrange them into clusters according to its correlation with the topic. The knowledge extracted from this analysis is the association of a particular method with a topic. Findings of this analysis provide an answer for questions like "what kind of approach is taken to solve a particular research question?"

We find game theory is the preferred method for relation/behavioral analysis in supply chain. It is generally used for a firm's economics, information sharing decisions, revenue sharing problem, and supplier buyer relation management. Probabilistic approach, hypothesis testing, and scientific approach of economics

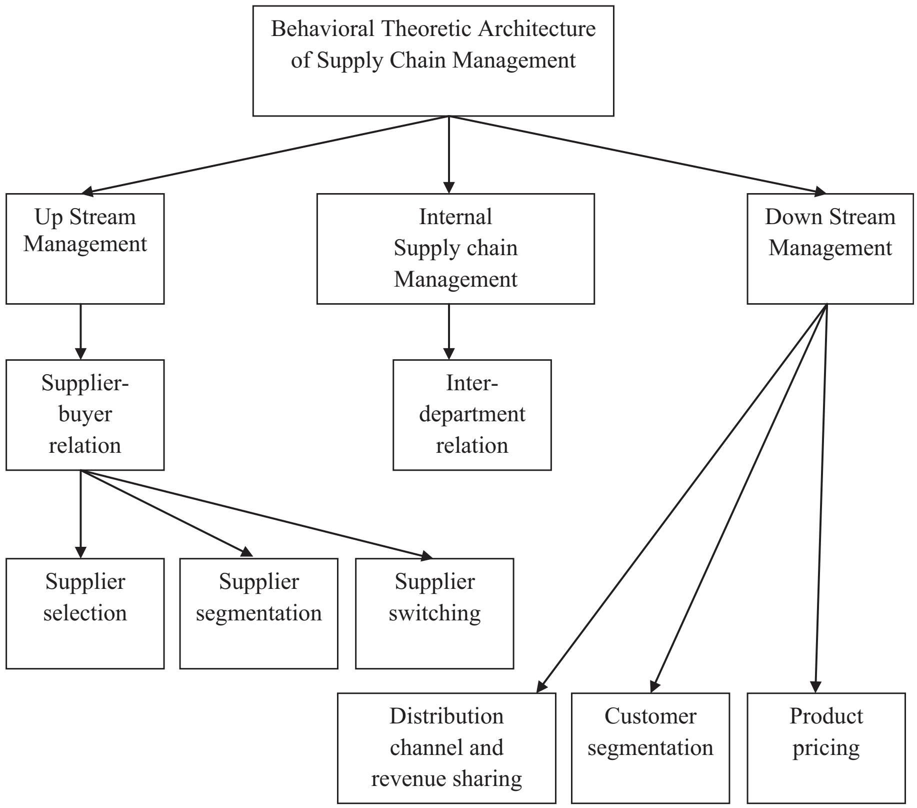

Fig. 9. Taxonomy of the research on behavioral operations in supply chain management.

were most used in the early decades for model development. Queuing theory was mostly used for service system design. Developing a framework, theory building for performance measure of manufacturing and production system is also identified through this analysis.

A computer based technique (simulation) was also noticed for human behavior analysis on decision. The use of an optimization model and algorithms are also noticeable in SCM. Branch and bound algorithm, integer programming, graph theory were mostly used in the early decades for transportation problems in the form of the traveling salesman problem. Integer programming, combinatorial optimization, neighborhood search, linear programming, risk based algorithms, and constraint programming are mostly used in vehicle routing, lot sizing, and facility location–allocation problem. Stochastic model, Markov process, and convex optimization techniques are also deployed for optimization of supply chain operations.

Further developments in computer science and algorithms like heuristic, metaheuristics, artificial intelligence enhanced research in various topics in SCM research. Metaheuristic approach like tabu search, simulated annealing, smart hill-climbing algorithm, non-dominated solution search methods, bacterial algorithms being used for the same purpose such as, vehicle routing, lot sizing, and facility planning. We have also noticed the use of UML and petrinet for supply chain modeling.

4.3. Developing a taxonomy of research on behavioral operations in SCM

Taxonomy of research on power influences in SCM has been developed based on the LSA of SCM research. LSA provides an overall view whereas reading and comprehending full papers of a specific area helped to develop insight about the domain. We have divided the research on behavioral operation in SCM into three categories i.e., upstream SC, internal SC, and downstream SC. The classified bases of the research are presented in Fig. 9. The research gap in these particular domains is considered in the next section.

4.4. Future research direction in behavioral operations in supply chain

Following is a glimpse of future research scope of this research domain. We will follow the proposed taxonomy as a sequence to present the research gaps. The notional SC as presented by Forrester (1961) is formed in four levels: retailer, wholesaler, distributor and manufacturer. The basic building block of SC lies in its network structure. SC simulation gives a deep insight for developing knowledge about the system. It helps to determine a cause-effect analysis (or what if analysis) of optimization and robustness of a strategy without interrupting the real SC execution. We propose system dynamics as a potential problem solving technique for research in the supply chains.

One can find an ample number of works in supplier buyer relation. Most of the research is on trust between supplier buyer, commitment of suppliers, conflict and conflict resolution between them. There are a few articles which consider inequality of power between supplier and buyer. Dominating power has been studied on the basis of dyadic relationship between two players. There is an unabridged gap between the study of dominating power and SC collaboration. So, the study of dominating power in a SC under various business scenarios has research scope.

Supplier selection has been an important issue for tactical decision making in the SCM. Multi-criteria decision making, fuzzy rules for supplier evaluation, and other heuristic methods are presented in literature to solve this problem. Most of the methods are used for quantitative analysis. The need for more research on qualitative analysis is still agile. Supplier segmentation is applied for decision making regarding relational investments with suppliers (e.g., human resources, technology, capacity building). In the long-term,

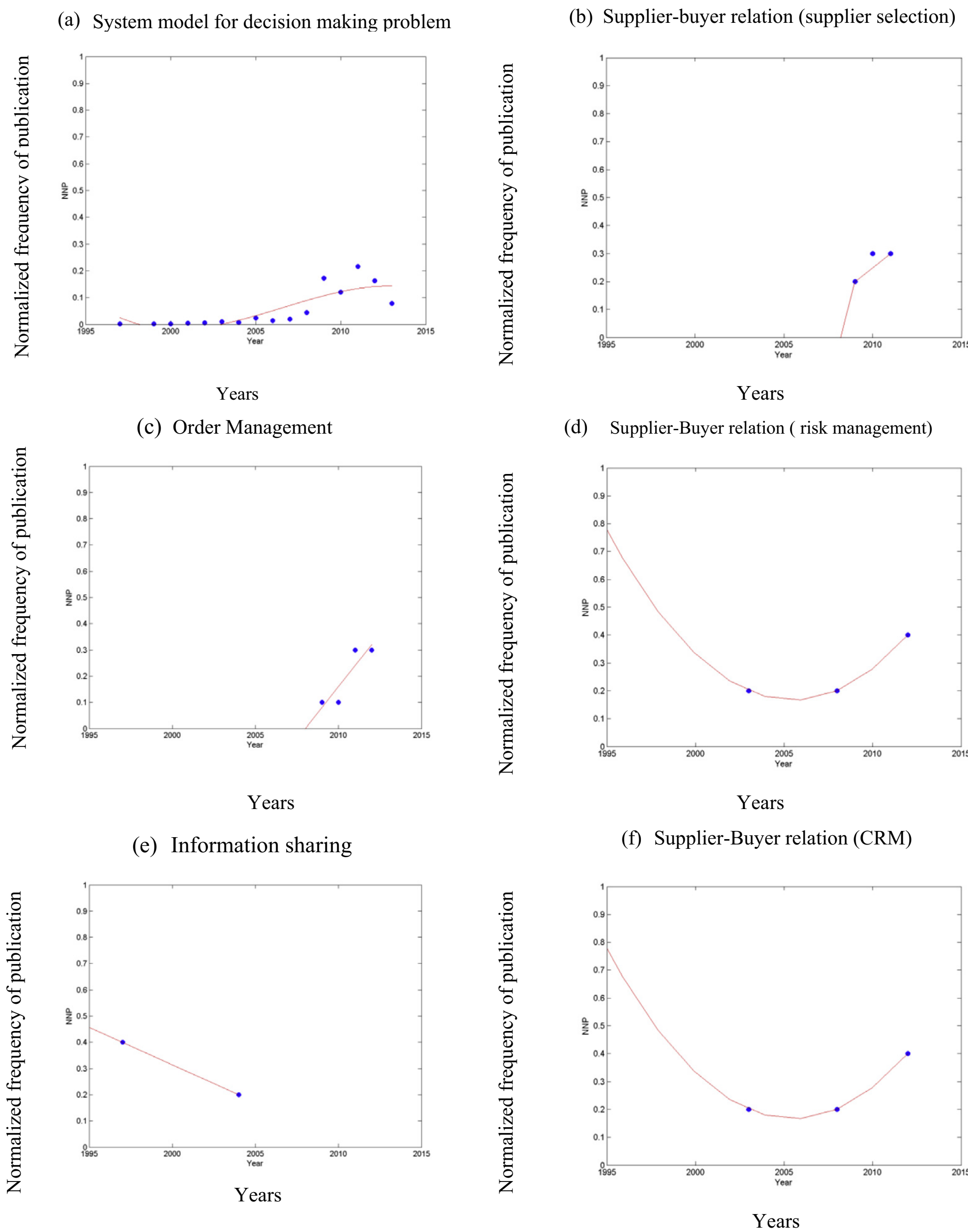

Fig. 10. Trend analysis of highly loaded topics related to supply chain for the period 1995 to 2015 published in ESWA Journal.

segmentation practices are applied to evaluate the development of the relationship over time. We find a scope of research in application of computational intelligence to improve supplier segmentation process. The research on supplier switching is new compared to supplier selection and segmentation. It is more often practiced in a dynamic supply chain. A select study on criteria selection for switching a supplier is essential. Finding a threshold value for such criterion to switch supplier also needs to be addressed. How supplier switching will affect flexibility, agility, and resilience behavior of SC is itself an open question for research.

While talking about competitive advantage, discussions are always getting inclined to global sourcing strategies. However, there is limited research reported in literature which dealt with supplier buyer behavioral analysis for sourcing decisions. We can relate sourcing with an internal supply chain also. In that case, two departments will act as two parties of SC. The behavioral analysis of how SC performance is related to the interdependency of players can be explored in this context.

The issues related to SC downstream are management of distribution channel, revenue sharing, customer segmentation, and product pricing. Computational intelligence facilitates analysis of issues in distribution channel design. Different variants of data mining are used to analyze customer behavior and consequently help forecasting demand. These tools are generally deployed to extract knowledge from structured and unstructured data available over internet. This analysis helps mitigate risk (distribution disruption, deviation, and post-disaster risk). Similarly it can also be used to increase resilience of SC. Customer segmentation, customer behavior analysis is one side of demand management. The other side is positioning a product into market, or customer, segment. Product pricing is one of the major criteria (decision variable) to target certain customer segments. Behavioral analysis of customer demand will be helpful to position a product into market. There is a scope to address such issues for different types of supply chains.

Overall, we have noticed a possible paradigm shift in supply chain research from data driven to behavior driven research. The more we incorporate behavioral aspects into decision support system, the more a correct solution can be obtained. Finally, concepts like Big Data, Internet of things, Ubiquitous positioning is going to empower research of behavioral operations in supply chain management.

4.4.1. Future research direction of supply chain in ESWA Journal

The research on supply chain has had a significant presence in ESWA Journal over the last two decades. We have collected abstracts of all published articles on supply chain in ESWA Journal in the 1995 to 2014 period. The distribution for a total of 849 articles over the decades has been already presented in Table 6. These abstracts have been analyzed and clustered into core topics. Fig. 10 shows the trend of past and present publication on SC in ESWA Journal.

A majority of the articles (highly loaded through document loading) have focused on System model for decision making problem, Supplier buyer relation, Order management. The type of research in supplier–buyer relation can be further sub-clustered into supplier selection, risk management, and customer relationship management (CRM). This depicts that the research related to human aspect in decision making and supply chain have been getting outlet in ESWA Journal. This also indicates the uniqueness of ESWA and shows that it always stays connected with emerging trend.

We expect more articles from the ESWA community on the application of expert system to analyze behavioral decision making. Having guided by the taxonomy presented here in this paper, we recommend to focus on supplier segmentation and supplier switching. Data-mining has been found as a potential tool to extract knowledge. Application of this approach has the potential to support decision making to protect supply chain against risk. It can also be applied to perceived customer behavior and to identify relational vulnerabilities. This will help to improve operations such as customer segmentation. These recommendations may encourage researchers to publish in ESWA.

5. Conclusions

We have presented a review of literature on supply chain as it began in 1934 and developed over eight decades of supply chain management research. In this study we have reviewed a long time horizon (80 years) with a highly diversified domain of research. A list of reputed journals and search results from Science Direct and Web of Knowledge, IEEE Xplore, and INFORMS is used to prepare the content collection of approximately 11,000 journal articles. Latent Semantic Analysis (LSA) is used as the review and knowledge extraction methodology. Using this text analysis method we can combine statistical methods and expert judgment to extract knowledge in the form of significant latent factors. These factors are footprints of development in this particular domain across the journey from normative to behavioral supply chain. We also propose taxonomy for supply chain management from behavioral context.

The behavioral operation which is more oriented towards the interaction of human behaviors and operational systems and processes, requires knowledge from cognitive psychology, social psychology, group dynamics, and system dynamics. Our motive was to present the journey from normative to behavioral issues researched in SCM, rather than be confined only to the behavioral aspect of operations in supply chains.

In summary, we believe research on behavioral issues will open windows into a wide range of analysis to supply chain managers. Our taxonomy provides one method for identifying implicit behavioral issues in SC models. The results presented are useful to have a holistic view of supply chain research and depicts a development in knowledge from outside the formal training to an intrepid researcher to venture into new terrain. We look forward to the emergence of research as well as literature reviews, in future.

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