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Decision-making models and support systems for supply chain risk: literature mapping and future research agenda

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ABSTRACT

Supply chain disruptions have serious consequences for society and this has made supply chain risk management (SCRM) an attractive area for researchers and managers. In this paper, we use an objective literature mapping approach to identify, classify, and analyze decision-making models and support systems for SCRM, providing an agenda for future research. Through bibliometric networks of articles published in the Scopus database, we analyze the most influential decision-making models and support systems for SCRM, evaluate the main areas of current research, and provide insights for future research in this field. The main results are the following: we found that the identity of the area is structured in three groups of risk decision support models: (i) quantitative multicriteria decision models, (ii) stochastic decision-making models, and (iii) computational simulation/optimization models. We mapped six current research clusters: (i) conceptual and qualitative risk models, (ii) upstream supply chain risk models, (iii) downstream supply chain risk models, (iv) supply chain sustainability risk models, (v) stochastic and multicriteria decision risk models, and (vi) emerging techniques risk models. We identified seven future research clusters, with insights from further studies for: (i) tools to operate SCRM data, (ii) validation of risk models, (iii) computational improvement for data analysis, (iv) multi-level and multi-period supply chains, (v) agrifood risks, (vi) energy risks and (vii) sustainability risks. Finally, the future research agenda should prioritize SCRM's holistic vision, the relationship between Big Data, Industry 4.0 and SCRM, as well as emerging social and environmental risks.

1. Introduction

Risks and uncertainties affecting supply chains are associated with demand, suppliers, cost, delivery, natural disasters, human failures, technical boundaries and cyber incidents that can result in significant losses to society. Because of this, many scholars have developed decision-making models and support systems for supply chain risk management (SCRM). The SCRM results from coordination or collaboration between supply chain partners to ensure profitability and continuity, and it encompasses two dimensions: operational and breach risks; and risk mitigation (Tang, 2006). According to Heckmann, Comes, and Nickel (2015) SCRM is typically considered as an event-oriented concept with two common components of probability of occurrence and related consequences.

Research on SCRM can be done using different approaches, methods and data collection techniques, for example: based on holistic vision (Bak, 2018; Fan & Stevenson, 2018; Oliveira, Espindola, & Marins, 2017; Prakash, Soni, Pal, & Rathore, 2017; Zhu, Krikke, & Caniëls, 2017); risk mitigation (Bandaly, Shanker, & Kahyaoglu, 2013; Kilubi & Haasis, 2015; Rajagopal, Shanmugam, & Goh, 2017; Snyder et al., 2016; Son, 2018); risk modeling (Fahimnia, Tang, Davarzani, & Sarkis, 2015; Heckmann et al., 2015; Ho, Zheng, Yildiz, & Talluri, 2015; Kilubi, 2016; Septiani, Marimin, Herdiyeni, & Haditjaroko, 2016); risk measurement (Aloini, Dulmin, Mininno, & Ponticelli, 2012; Bandaly et al., 2013; Chiu & Choi, 2013;

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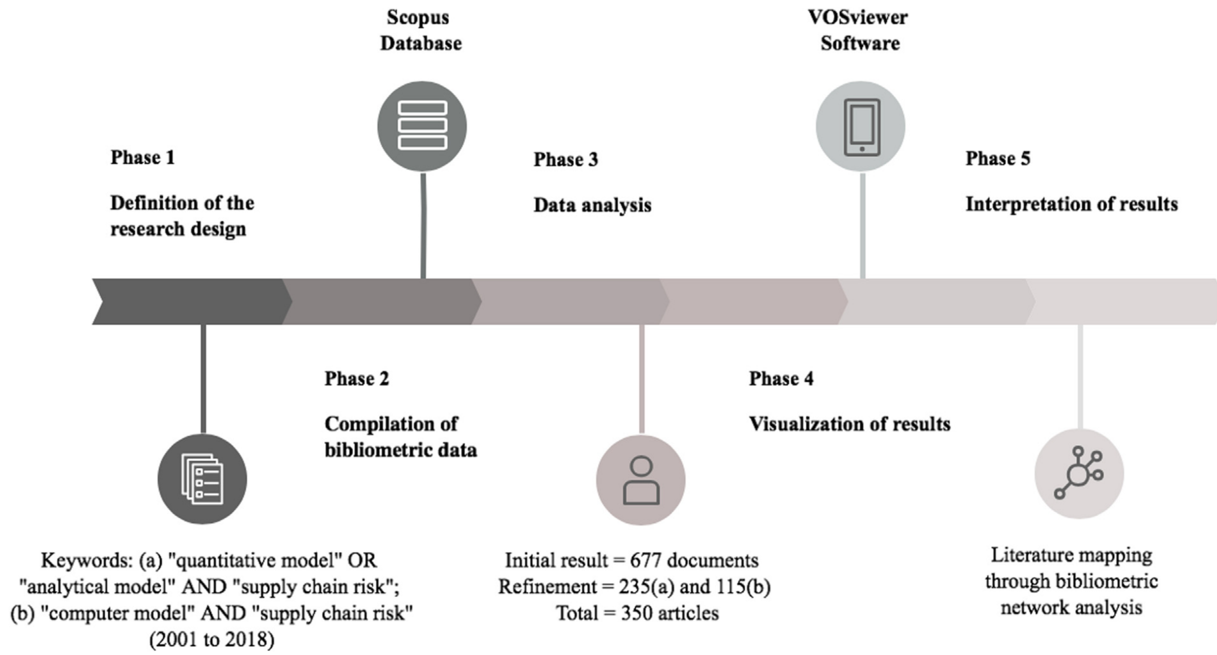

Fig. 1. Phases of the literature mapping methodology.

Klibi, Martel, & Guitouni, 2010; Tomas & Alcantara, 2013); decision/attitude risks (Heckmann et al., 2015; Manuj & Mentzer, 2008; Olson & Wu, 2010; Rao & Goldsby, 2009; Tang, 2006); and network analysis (Colicchia & Strozzi, 2012; Fahimnia, Tang et al., 2015; Ghadge, Dani, & Kalawsky, 2012; Rajagopal et al., 2017; Tang & Musa, 2011).

For Jüttner, Peck, and Christopher (2003), most SCRM study approaches can be framed in positive and normative research methods. Positive research seeks to describe, explain, predict, and understand SCRM activities. These include qualitative methods such as in-depth interviews and case studies. In contrast, normative research attempts to prescribe what organizations and individuals should do with regard to SCRM, such as studies on decision-making models and decision support systems. SCRM modeling is an important area of research because its prescriptive nature can be extremely beneficial for the development of decision-making tools and support systems oriented towards competitive advantage.

In this article we use an objective and innovative approach to map the literature and establish a future research agenda on decision-making models and support systems for SCRM. More specifically, we analyze the most influential decision-making models and support systems for SCRM, evaluate the main areas of current research, and offer insights for future research in the field. To this end, we collected and examined 350 decision modeling and support system documents for SCRM published in the Scopus database.

The rest of this paper is organized as follows: in topic 2 we present the study methodology, in topic 3 we demonstrate the results of literary mapping through bibliometric network analysis. We discuss the gaps in the studies and propose a future research agenda in topic 4. Finally, we present the conclusions, recommendations and limitations of research in topic 5.

2. Literature mapping methodology

Bibliometric methods introduce a measure of objectivity in scientific assessment, attenuating bias and aggregating opinions of various researchers. Zupic and Cater (2015) proposed a five-phase methodology for critical literature mapping, promoting the identification of gaps and the generation of research insights in a given area of knowledge: 1. definition of the research design and method; 2. compilation of bibliometric data; 3. data analysis; 4. visualization of results; and 5. interpretation of results. In this article, we adopted a similar systematic literature mapping process to analyze the most influential decision-making models and support systems for SCRM, evaluate the main areas of current research, and offer insights for future research in the field.

2.1. Definition of keywords and initial refinement of data

To achievement of study objectives, two keyword combinations were defined: (a) "quantitative model" OR "analytical model" AND "supply chain risk"; and (b) "computer model" AND "supply chain risk". The bibliographic data collection was done in the Scopus database which is the largest database of abstracts and citations of peer-reviewed research literature in various fields of knowledge. Keywords were searched for 'title, abstract, keywords' in documents published between 2001 and 2018. The initial search yielded 677 documents which were refined to eliminate conference articles, books and trade publications, limiting the data set to only articles written in English and published in specialized journals. After this, the search yielded 235 articles for word combination (a) and 115 articles for word combination (b), totaling 350 publications. These results were stored in CSV format (containing title, authors, abstract, keywords and references) for further analysis in bibliometric networks. Fig. 1 presents the phases of this literature mapping process.

2.2. Data analysis strategy

We adopted an inductive approach in this article for data analysis purposes (Fahimnia, Tang et al., 2015; Fahimnia, Sarkis, & Davarzani, 2015; Mishra, Gunasekaran, Papadopoulos, & Childe, 2016; Seuring & Müller, 2008). The literary mapping of studied field was done using the bibliometric network analysis technique, according to Fig. 1. The mapping and analysis of bibliometric networks aim to show the structural and dynamic aspects of scientific research (Cobo, Lopez-Herrera, Herrera-Viedma, & Herrera, 2011).

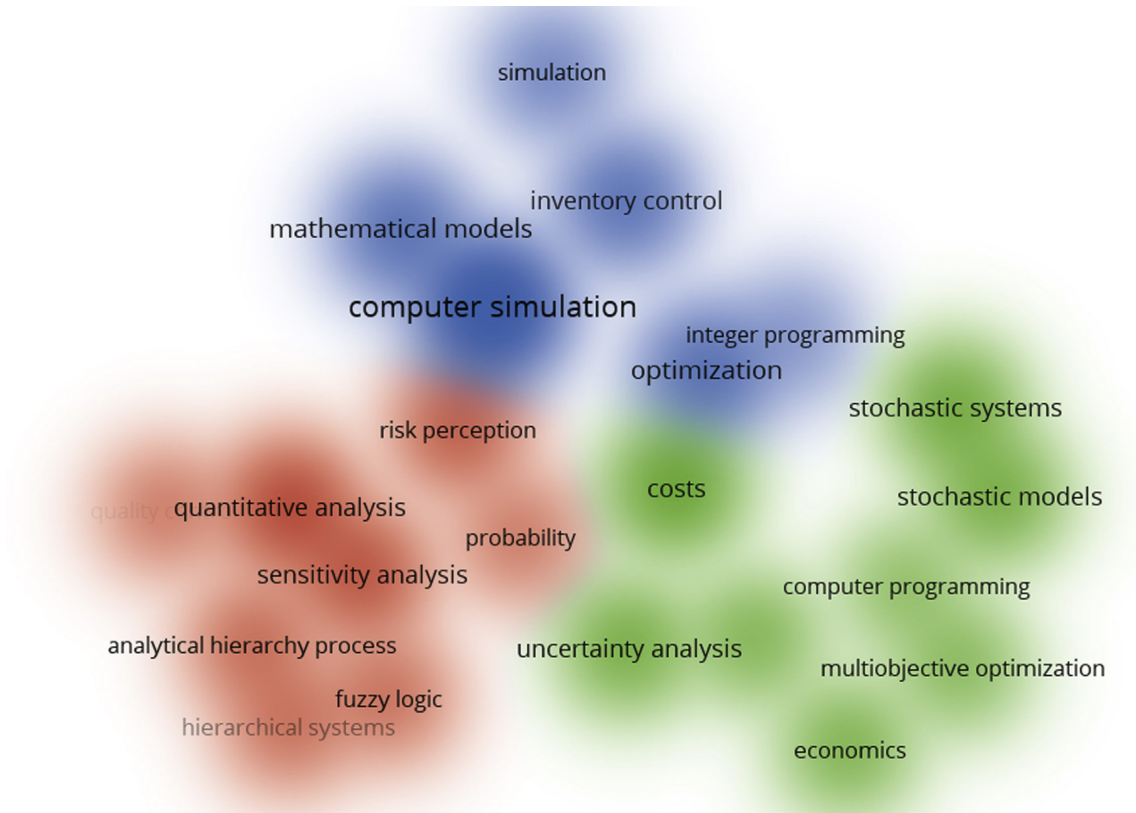

Fig. 2. VOSviewer network of co-word on decision-making models and support systems for SCRM.

Critical literature mapping was done with the aid of VOSviewer software, version 1.6.11. The choice of VOSviewer was justified by the fact that besides providing the construction and visualization of bibliometric networks, it can also handle large data sets, producing a variety of visualization, analysis, and search options (Van Eck & Waltman, 2014 and 2017).

3. Literature mapping through bibliometric network analysis

A bibliometric network consists of nodes and edges. Nodes can be for example publications, journals or authors, and edges indicate relationships between pairs of nodes. In the VOSviewer software the nodes in a bibliometric network are positioned in such a way that the distance between two nodes roughly indicates the degree of kinship between them (visualization of similarities technique - VOS). In general, the smaller the distance between two nodes, the greater their relationship. Building a network map in VOSviewer consists of three steps: first, a similarity matrix is calculated based on the co-occurrence matrix; second, a map is constructed applying the VOS mapping technique to the similarity matrix; and third, the map is translated, rotated and reflected.

VOSviewer software also designates nodes in a network of clusters. A cluster is a set of closely related nodes. VOSviewer uses colors to indicate the cluster to which a node has been assigned and the number of clusters is determined by a resolution parameter. It uses a grouping technique defined by a smart local moving algorithm (more information about this see Van Eck & Waltman, 2014 and 2017). After the nodes of a bibliometric network have been positioned in a two-dimensional space and assigned to clusters, the network can be displayed.

The data in the articles selected from the Scopus base were inserted in the VOSviewer software in the CSV format to analyze the bibliographic networks. Initially, we mapped the intellectual structure of the most influential decision-making models and support systems for SCRM. For this, we used the co-word analysis technique, which according to Sidorova, Evangelopoulos, Valacich, and Ramakrishnan (2008) helps to reveal and build the identity of a discipline. The VOSviewer's 'co-ocorrence' map with unit of analysis 'all keywords' and method 'full counting' identified 3982 keywords in all articles selected. We decided to require a minimum of ten citations so that each keyword could be included in the co-word network, thus obtaining 58 terms. After this, we excluded those that did not specifically refer to decision-making models and support systems for SCRM. In the end, we obtained a set of 22 representative keywords. We calculated the total co-occurrence link strength of each of these keywords and allocated them into clusters, as shown in Fig. 2.

Fig. 2 shows three co-word network groups in SCRM decision making models and support systems: cluster 1 (red) made up of "quantitative multicriteria decision models", cluster 2 (green) made up of "stochastic decision-making models" and cluster 3 (blue) made up of "computational simulation and optimization models".

Cluster 1 consists of eight quantitative multicriteria decision models. Because of the competitiveness of markets and the increasing application of organizational and manufacturing philosophies such as Just-in-Time (JIT) and Total Quality Management (TQM), various multicriteria decision making models (MCDM) have been developed to address supply chain risks (Simić, Kovačević, Svirčević, & Simić, 2016). When mapping the literature using the co-word technique, we found that the main methods used for multicriteria decision making have been: Quantitative Analysis (n = 25), Sensitivity Analysis (n = 20), Risk Perception (n = 17), Analytical Hierarchy Process—AHP (n = 13), Fuzzy Logic (n = 12), Hierarchical Systems (n = 12), Probability (n = 10) and Quality Control (n = 10).

Cluster 2 is made up of eight stochastic decision-making models. The stochastic approach is appropriate for SCRM because it

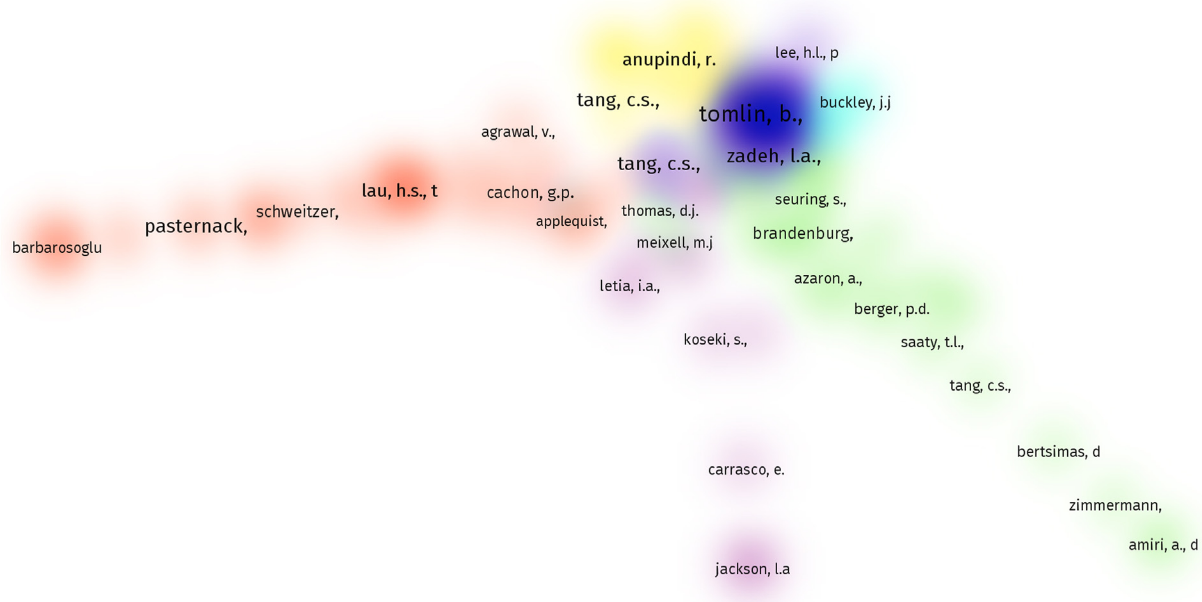

Fig. 3. VOSviewer network of co-citation on decision-making models and support systems for SCRM.

considers the uncertain nature of events, assuming that probability distributions of certain events are known or can be estimated. Stochastic programming models involve dynamic decision-making and have several applications in cost, econometrics, computational and statistical simulations (Goh, Lim, & Meng, 2007). The main techniques in this group were: Costs (n = 25), Sthocastic Systems (n = 20), Uncertainty Analysis (n = 18), Stochastic Models (n = 18), Economics (n = 15), Monte Carlo Methods (n = 14), Multiobjective Optimization (n = 12) and Computer Programming (n = 10).

Cluster 3 is composed of six computational simulation and optimization models. Increasingly, SCRM has been assisted by models based on computational intelligence. Computational optimization tools are usually based on advanced mathematical models that simulate human decisions and have many applications in the supply chain. The main approaches in this grouping were: Computer Simulation (n = 66), Optimization (n = 27), Mathematical Models (n = 26), Inventory Control (n = 25), Simulation (n = 15) and Integer Programming (n = 10). Therefore, clusters 1, 2 and 3 of the co-word network reflect the mapping of most influential techniques and methods in the field of decision-making models and support systems for SCRM.

To evaluate the key areas in which decision-making models and support systems for SCRM are employed, we adopted the bibliometric method of co-citation analysis. It uses measures of similarity, defining the frequency with which two units are quoted together (Small, 1973; White & McCain, 1998). To create the co-citation map of articles obtained from the Scopus database, we also built a VOSviewer's bibliographic data network (analysis unit 'cited references' and 'counting fractional'). Initially, we identified about 16,000 cited references. We set the minimum two-citation criterion for a publication to be included in the co-citation network, resulting in 407 references. However, to ensure integrated analysis, we chose to show only the set of interconnected items, that is, 381 references, as shown in Fig. 3. For each of these references we calculated the total strength of the co-citation link.

Using VOSviewer software we identified six clusters in the co-citation network—indicated by the colors shown in Fig. 3 (we opted for the cluster resolution parameter 0.50, as it is more appropriate for aggregate data analysis). The contents and areas of the articles were carefully examined to discover the research focus area of each of the six clusters. Below, we show the main publications and content of each cluster: cluster 1 (dark blue color/made up of 145 articles, top five publications—Tomlin, 2006; Kleindorfer & Saad, 2005; Tang, 2006; Hendricks & Singhal, 2005; and Craighead, Blackhurst, Rungtusanatham, & Handfield, 2007), characterized as the most popular and diversified, contributed mainly with theoretical, methodological and literature review studies on SCRM. This group emphasized several conceptual and qualitative models that prioritized risk mitigation, contingency strategies and supply chain resilience; cluster 2 (yellow/63 items, top articles—Anupindi & Akella, 1993; Christopher & Lee, 2004; Gürler & Parlar, 1997; Sheffi, 2001; and Kern, Moser, Hartmann, & Moder, 2012) mainly emphasized the upstream supply chain risk modeling (supply uncertainty, inventory replacement and supplier evaluation problems), and discussed operational analytical approaches for the identification, evaluation and mitigation of risks.

Next, cluster 3 (red/57 items, main papers—Pasternack, 2008; Lau, 1980; Eeckhoudt, Gollier, & Schlesinger, 1995; Wang & Webster, 2007; and Schweitzer & Cachon, 2000) focused on downstream supply chain risk modeling, addressing issues of demand uncertainty (analytical and behavioral aspects of the risks of inventory decision making, contracts, price, cost, profits and losses in the process of coordinating of the supply chain); cluster 4 (green/56 items, top articles—Heckmann et al., 2015; Brandenburg, Govindan, Sarkis, & Seuring, 2014; Seuring, 2013; Fahimnia, Sarkis, et al., 2015; and Carter & Rogers, 2008) addressed the quantitative modeling of sustainability risks in the supply chain (reviews on sustainability and frameworks for social and environmental management of supply chains).

Cluster 5 (light blue/39 articles, main papers—Zadeh, 1965; Benyoucef et al., 2003; Chan & Kumar, 2007; Chen, Lin, & Huang, 2006; and Chen, 2000) emphasized the use of stochastic modeling and multicriteria decision support, especially applied to situations of supplier selection risks. The most used multicriteria decision support methods in this group were the Analytical Hierarchy Process—AHP, Fuzzy Logic and the Technique for Order Preference by Similarity to Ideal Solution—TOPSIS; finally, cluster 6 (purple/21 items, top articles—Tuncel & Alpan, 2010; Kumar, Tiwari, & Babiceanu, 2010; Faisal, Banwet, & Shankar, 2006; Diabat, Govindan, & Panicker, 2011; and Yang & Yang, 2010) focused on the development of emerging modeling techniques, such as Interpre-

Table 1
Main results of literature mapping through bibliometric network analysis.

Co-word network			Co-citation network		
Cluster	N. Methods	Decision-making models most influential	Cluster	N. Articles	Key areas in current research
1	8	Quantitative multicriteria decision models	1	145	Conceptual and qualitative risk models
2	8	Stochastic decision-making models	2	63	Upstream supply chain risk models
3	6	Computational simulation/optimization models	3	57	Downstream supply chain risk models
–	–	–	4	56	Supply chain sustainability risk models
–	–	–	5	39	Stochastic and multicriteria decision risk models
–	–	–	6	21	Emerging techniques risk models

Bibliographic coupling network			
Cluster	N. Articles	Research front	Insights for future research
1	61	Conceptual and qualitative risk models	Develop tools to operate larger volumes of SCRM data
2	40	Emerging techniques risk models	Validate quantitative and analytical risk models
3	35	Upstream supply chain risk models	Improve computational processing for data analysis
4	32	Downstream supply chain risk models	Address multi-level and multi-period supply chains, and conduct risk behavioral experiments
5	24	Food supply chain risk models	Develop technological solutions for evaluation and treatment of microbiological risks
6	10	Energy supply chain risk models	Improve risk optimization models and technologies
7	6	Supply chain sustainability risk models	Develop risk studies for environmental and social sustainability

tive Structural Modeling (ISM), Petri Net Analysis, and techniques of computational intelligence such as genetic algorithms and artificial neural networks.

To provide insights for future research on decision-making models and support systems for SCRM we adopted the bibliographic coupling analysis. This uses the number of references shared by two documents as a measure of similarity between them (Kessler, 1963) and is recommended to map a research front (Small, 1999). We created a map of bibliographic coupling (analysis unit 'documents' and 'counting fractioned') and chose two citations for each article. As a result, we obtained 208 interlinked articles. VOSviewer produced bibliographic coupling network with seven clusters (resolution parameter of 0.50). The content and areas of the articles in each cluster were analyzed to map the current research front and the recommendations for further investigation.

The current research front of cluster 1 (61 articles, top five—Fahimnia, Tang et al., 2015; Yildiz, Yoon, Talluri, & Ho, 2016; Colicchia & Strozzi, 2012; Faisal, 2009; and Son & Orchard, 2013) is related to supply chain risk modeling conceptualization. Costs and reliability risk, susceptibility and risk mitigation, as well creation and dissemination of knowledge for SCRM were the main themes addressed. The key future research suggestions are the development of advanced analytical and computational tools to operate larger volumes of theoretical and practical data on SCRM; cluster 2 (40 papers, top five—Khan & Burnes, 2007; Sharma & Routroy, 2016; Mizgier, Wagner, & Holyst, 2012; Kim, 2011; and Hwarng, Chong, Xie, & Burgess, 2007) dealt the application of emerging techniques for supply chain risks quantification, such as Bayesian Networks Modeling, Agent-based Modeling (ABM), Quantity-Flexibility (QF), modeling and simulation, Transaction Cost Theory, Petri Nets Analysis, Radio Frequency Technology (RFID), computational intelligence, etc. The further studies refer to the need for broader empirical studies and in different contexts for the validation of the proposed models.

Cluster 3 (35 publications, top five—Wang, Li, & Shi, 2011; Chan, Kumar, Tiwari, Lau, & Choy, 2008; Chan & Kumar, 2007; Moghaddam, 2015; and Wang, Chan, Yee, & Rainey, 2012) developed risk studies using stochastic approaches, with multivariate analysis and mainly multicriteria decision analysis, with an emphasis on AHP and Fuzzy methods (in problems related to the selection of suppliers and operational location). The recommendations for future research in this group refer to the need to expand the scope of supply chain variables and improve computational processing capacity for complex risk analysis; cluster 4 (32 papers, top five—Tang, 2006; Chiu & Choi, 2013; Arshinder, Kanda, & Deshmukh, 2009; Arcelus, Kumar, & Srinivasan, 2012; and Arshinder, Kanda, & Deshmukh, 2009.) discussed issues related to the quantification of pricing risks, stochastic demand and supply levels. Robust mathematical and analytical models based on extensions of Newsboy Model, Game Theory, and econometrics simulation/optimization were discussed in the treatment of risks in uncertain environments. The recommendations for future research indicate the need to approach networks of supply chains from a multilevel and multi-period approach, as well as experiments on risk and decision making behavior.

Clusters 5, 6 and 7 correspond to research on supply chain risk modeling that begins to be structured in specific fields. Cluster 5 (24 items, main papers—Franz, Tromp, Rijgersberg, & van der Fels-klerx, 2010; Manning & Soon, 2013; Septiani et al., 2016; Tromp, Rijgersberg, & Franz, 2010; and Jacxsens et al., 2010) addressed the risk modeling of the food supply chain. Some of the most used models for the statistical risk assessment were Quantitative Microbiological Risk Assessment (QMRA), Food Safety Risk Assessment (FRAMp) and Safe Foods. The opportunities for future research refer to new technological solutions for the microbiological evaluation of pre and post-harvest; cluster 6 (10 articles, top five—Fang, Liao, & Xie, 2015; Gebreslassie, Yao, & You, 2012; Santibañez-Aguilar et al., 2016; Chen, Chen, & Che, 2008; and Pan, Liu, & Li, 2017) focused on risk modeling of the supply chain of energy (mainly hydrocarbons and biofuels). The approaches used were multicriteria stochastic programming, Bayesian Networks, and economic-financial evaluation (Value-at-Risk—VaR, Conditional Value-at-Risk—CVaR, etc.). Future investigations referred to improvement in risk models to increase the optimization of the world's energy systems.

Finally, cluster 7 (6 papers, top five—Kull, Oke, & Dooley, 2014; He, 2015; Abbey, Kleber, Souza, & Voigt, 2017; Kianpour et al., 2017; and Wang & Chen, 2015) concentrated on the modeling of the risks of recycling, remanufacturing and reverse logistics. The modeling used was closed-loop supply chain (CLSC), pricing of remanufactured products, consumption in reuse, repair and recycling, and product life cycle analysis. Suggestions for future research involved risks to environmental and social sustainability.

4. Discussion of results and proposed future research agenda

The results of mapping the literature on SCRM decision-making models and support systems contribute significantly to the research agenda and professional practice in this area, as shown in Table 1.

Through the co-words network we identified three main groups of decision support models that reflect the intellectual identity of the area: 1. quantitative multicriteria decision models, 2. stochastic decision-making models and 3. computational simulation and optimization models. This finding serves as a reference for researchers and professionals interested in studying and/or implementing techniques and quantitative methods already validated in the supply chain risk area.

We mapped and analyzed six current research clusters: cluster 1 is the most popular, clusters 2–5 have received considerable attention from researchers, while cluster 6 has a broader scope for future works. Regarding the seven future research clusters, we found that: cluster 1 (supply chain risk conceptualization) is the first step in the implementation of the supply chain risk models of clusters 2, 3 and 4. The improvement of risk modeling of clusters 2, 3 and 4 is crucial for the creation of robust technological tools to risk management in food (cluster 5), energy (cluster 6) and sustainability (cluster 7). Future research into SCRM modeling should include these seven groups, which presupposes the need to develop risk models for various segments of society—the SCRM holistic vision.

Computational development should enable further research with the importance of analytical tools and SCRM Big Data technologies (Brown, Chul, & Manyika, 2011; Davenport, 2006; McAfee & Brynjolfsson, 2012). Thus, future studies may also consider the ability of Big Data Analytics to improve the efficiency of SCRM, inserting enterprises in the context of Industry 4.0 (Hazen, Boone, Ezell, & Jones-Farmer, 2014; Fan, Heilig, & Voss, 2015; Sanders & Ganeshan, 2015; Schoenherr & Speier-Pero, 2015; Mishra et al., 2016; Wang, Gunasekaran, Ngai, & Papadopoulos, 2016; Kache & Seuring, 2017; Zhong, Xu, Klotz, & Newman, 2017). Finally, we find that sustainable SCRM is an area with recent substantial growth. It is the most emergent research flow in SCRM modeling area with great potential for researchers to make important contributions to themes such as recycling, remanufacturing, reverse logistics and environmental and social risk (Brandenburg et al., 2014; Carter & Rogers, 2008; Seuring & Müller, 2008; Seuring, 2013; Tang & Zhou, 2012; and Fahimnia, Sarkis et al., 2015).

5. Conclusions, recommendations and limitations

Supply chain risk management (SCRM) has become a thriving area of research and professional practice. Thus, it is extremely relevant to identify, classify and analyze works and trends in this field. By adopting objective bibliometric measures through co-word, co-citation and bibliographic coupling networks we can reveal the literary identity of the field, map key areas in which decision models and support systems are developed and applied, and highlight insights from future research to help give researchers and practitioners a clear view of the past, present and future of SCRM.

These results have three main consequences: first, researchers and managers can improve the holistic view of SCRM by understanding mature and emerging themes in the field; second, the claim for computational enhancement reveals the need to incorporate Big Data, Internet-of-Things (IoT), Artificial Intelligence, and Industry 4.0 methods and tools into the scope of SCRM; and third, the substantial growth in sustainable supply chain management reflects the need for new studies and business models particularly focused on social and environmental aspects.

However, the literature mapping adopted in this article has some limitations. The first refers to the choice of keywords, that is, we use general terms to capture the decision support models in the SCRM instead of specific names of techniques and tools, which could generate a larger number of documents on the subject. On the other hand, a larger number of documents could restrict the processing capacity of the adopted software, besides reducing some detailed inferences on the subject. Another limitation refers to the classification that we carried out through groupings which are not necessarily homogeneous, since there are different themes in some categorized areas, suggesting the possibility of more evaluations and interpretations.

Finally, the bibliometric methods presented are unable to "interpret" the knowledge of the literature and explore the reasons why certain works have been central to the development of the area (syntax vs. semantics). As bibliometric techniques and tools are improved, new opportunities for literary and empirical research on SCRM will arise. Despite these limitations, we believe that this article will promote the interest and reflection of researchers and professionals working in the supply chain field.

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