Quantitative and Qualitative Models for Managing Risk Interdependencies in Supply Chain

A. Díaz-Curbelo and A. M. Gento Municio

Abstract The interdependent nature of supply chain elements and events requires risk systems must be assessed as an interrelated framework to optimize their management and integrate effectively with other decision-making tools in uncertain environments. This research shows a synthesis and analysis of the main qualitative/quantitative methods that have been used in the literature considering the treatment of event dependencies in supply chain risk management in the period 2003–2018. The results revealed that the integration with disruption analysis tools and artificial intelligence methods are the most common types adopted, with increasing trend and effectiveness of Bayesian and fuzzy theory approaches.

Keywords Supply chain · Risk assessment · Dependency · Quantitative methods

1 Introduction

Integrated Supply Chain Management (SCM) is a major concern in today's competitive market environment. The last few decades have been characterized by significant changes in the SCM due to increased globalization and innovation rate. This global increase in Supply Chain (SC) relationships is associated with greater interconnection between suppliers and manufacturers, leading to greater dependence on SC companies and a higher level of complexity [1, 2]. In this sense, despite their large benefits, extended SCs are more vulnerable, exposing organizations to higher levels of risk. In this regard, risk management has emerged as a major research topic in the literature of Operations Management and SCM [3].

A. Díaz-Curbelo
Escuela de Ingenierías Industriales, Universidad de Valladolid, Valladolid, Spain
e-mail: alina.diaz@uva.es

A. M. Gento Municio (✉)
Dpt. Organización de Empresas Y CIM, Universidad de Valladolid, Paseo del Cauce 59, 47011 Valladolid, Spain
e-mail: gento@eii.uva.es

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A risk event can be caused by a set of risk factors and can lead to different impacts throughout the supply network [4]. It is necessary capturing the interdependencies between risk events under uncertainty. Therefore, effective supply chain risk management (SCRM) should take into account the systemic nature of risks in the form of events so that they can be modeled, assessed, treated and controlled.

Although several studies have reviewed the literature on SCRM methods [3, 5–8], in the knowledge of the authors, no precedent was found for a literature review specifically analyzing qualitative and quantitative methods for dependency management as a key factor in SCRM. Therefore, we have addressed the following research question: How can the relationships between risk events be treated to quantify the risk level to manage mitigation strategies effectively in uncertain SC environment?

For this purpose, we analyze documents that explicitly consider, model, and evaluate interdependencies risk events in the management of the SC. We focus on those published in academic and professional journals of high impact and we limited the research to the English language and a temporary space from 2003 to 2018. At the end of the methodological process followed, 107 articles were obtained to perform the analysis.

We organize this paper as follows: first, we summarize the methodology used to carry out the literature review and analysis; next, we show the analysis and discussion of the main qualitative and quantitative, individual and integrated SCRM methods; finally, concluding remarks on strengths and trends motivating future research.

2 Methodology

The general methodology used for the development of this research is shown in Fig. 1. For this purpose, the research methodology proposed by [9] was adapted, which allowed the identification and review of the relevant literature in the period

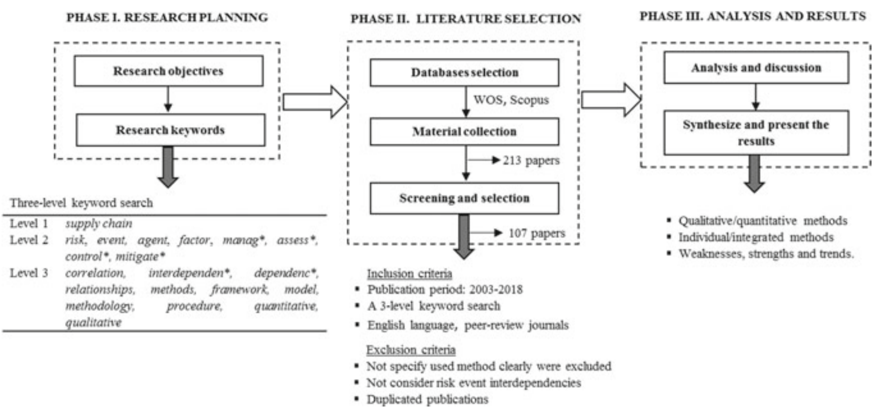

Fig. 1 Research methodology

2003–2018. According to [6], from 2003 onwards there has been a growth in the number of publications related to SCRM.

The analysis focused on documents that explicitly model, assess or manage risk in SCM considering interdependencies analysis. Research that did not consider event dependencies was excluded. We focused on those published in high impact academic and professional journals (SCOPUS and WOS), mostly in the areas of Operations Research and SCM. At the end of this process, 107 articles were obtained as a basis for the analysis.

3 Results and Discussion

The literature review made it possible to identify the main qualitative/quantitative, simple/integrated methods (Tables 1 and 2) that have been used in the literature with the perspective of dependency between SC risk events.

In the consulted literature, several models have been proposed to capture the interdependence between SC risks. As for the family of causal disruptive techniques, many methods have been designed for the identification and modeling of risks in manufacturing and service industries. Some of these methods have proven useful for assessing all types of risks. Examples of the most common methods are Event Tree (ET), Fault Tree Analysis (FTA) and Bow-Tie (BT).

In ET, qualitative analysis identifies possible outcome events from a source event, while quantitative analysis estimates the probability or frequency of the outcome event (probability) for the tree. Similar to ET, an FTA is a logical and graphical

Table 1 Summary of individual methods

Methods	References
ANP	[11, 12]
BN	[13–19]
BT	[10, 20–26]
Decision tree analysis	[27–30]
Disruption analysis network	[31]
FMEA	[32–43]
FTA	[15, 44–51]
Games theory	[52–54]
Hybrid PNs	[55]
Interpretive structural modeling	[56–58]
Multiple regression model	[59–61]
PN	[62, 63]
Simulation	[64, 65]
Supply network opportunity assessment package	[66]

representation that explores the interrelationships between a potentially disruptive event in a system and its causes. According to [10], a typical FTA consists of the main event, basic events and logic gates. The technique follows a top-down approach that is useful for brainstorming about causes and consequences.

An FTA can also be analyzed qualitatively and quantitatively. A quantitative analysis mathematically calculates the probability of occurrence of the main event, as well as other relevant numerical indices, e.g. the severity of the consequence. These estimates depend to a large extent on the availability of fault data. However, according to [95, 108], for most large and complex systems, it is often difficult to obtain accurate failure data due to lack of knowledge, scarce statistical data, and ambiguous system behavior.

In the same line of capturing the interdependence between risks in SC, fault and event trees can be integrated into the form of a BT diagram where the central event represents the release of a hazardous agent. For example, in [10] they used the BT model for risk management of seaports and offshore terminals, in [20] for accident analysis in a pharmaceutical production plant, and in [24] for risk analysis in the oil and gas industry. An interesting proposal is also of [79] who propose a model based on the BT method to see the interdependence of risks and a set of associated mitigation strategies in the high-end server manufacturing SC.

At the same time, Interpretive Structural Modeling (ISM) is a hierarchical technique that establishes the order and direction of complex relationships between the elements of a system. For example, in [56], it has been used to determine causal relationships between risk mitigation strategies. However, according to [72], these models do not explicitly capture the interdependence between risks.

Despite their extensive use, these traditional models have several limitations. The first is the assumption of statistical and stochastic independence between events, a limited focus on capturing data from common causes of failure. Another unrealistic assumption is to consider only binary states in the behavior of systems. It is also not considered a temporary behavior. However, in real-life systems, events present a more conditioned and complex dynamic. These assumptions can lead to an inadequate estimation of the reliability of the SC. In this sense, alternative approaches have been developed to mitigate these limitations.

In this sense, Bayesian networks and Petri nets are highlighted. These two different approaches are used as individual approaches or in association with other methods to address many of the limitations of classical approaches. The two approaches share capabilities such as enabling predictive analysis of system failure behavior taking into account statistical, stochastic, and temporal dependencies of events.

We can see the proposal of [87] with a timed PN-based approach for risk assessment and real-time control of SC networks. In this approach, the FMEA is used to identify disturbance factors in the SC, the dynamic and stochastic behavior of the SC is modeled using timed PNs. In [62], they use PNs for enterprise resource planning risk assessment taking into account the dependencies between different risk factors. Lee et al. [101] has proposed a PN framework for modeling and analyzing distributed manufacturing networks. In this case, a Monte Carlo simulation was used to validate the mitigation process. Guo et al. [103] propose a comprehensive risk assessment

Table 2 Summary of integrated methods

Methods	References
ANP; goal programming; fuzzy theory; analysis of five forces; value at risk	[67]
ANP; rough set theory	[68]
BN; ant colony optimization	[69]
BN; Bow-Tie analysis	[70, 71]
BN; FMEA	[17]
BN; FTA	[72]
BN; fuzzy theory; AHP	[73]
BN; fuzzy theory; FMEA	[74]
BN; interpretive structural modeling	[75]
BN; simulation	[76, 77]
BT; FMEA; fuzzy theory; Lean Manufacturing	[4]
BT; fuzzy theory	[24, 78, 79]
Capital asset pricing model; net present value; variational inequality model	[80]
Cluster analysis; factorial analysis	[81]
Decision tree; mathematical programming	[82]
Decision tree; simulation	[64, 65]
Economic value added; stochastic programming	[83]
ET; fuzzy theory	[84, 85]
FMEA; AHP	[38]
FMEA; AHP; experiment designs; discrete event simulation	[86]
FMEA; PN	[87]
FMEA; Quality Function Deployment (QFD)	[88]
FMEA; fuzzy theory	[89–94]
FTA; fuzzy theory	[95]
Genetic algorithms; statistical methods	[96]
Global production network; fuzzy theory; inoperability input–output model	[97]
Graph theory; life cycle inventory	[98]
Graph theory; supply chain vulnerability index	[99]
Lagrangian relaxation; integer non-linear programming model	[100]
PN; Monte Carlo simulation	[101]
PN; triangularization clustering algorithm	[102]
PN; fuzzy theory; AHP; Entropy method, cloud model	[103]
QFD; AHP	[104]
Radial basis function neural network; fuzzy theory	[105]
Regression models; exploratory factor analysis; reliability tests	[106]
SCOR model; AHP; fuzzy theory	[107]

framework based on diffuse PNs in combination with AHP, entropy and cloud model methods for long-distance transport pipelines.

At the same time, the use of BNs has increased rapidly due to their flexible structure and their reasoning capacity under uncertainty. The main advantage of BNs over other existing methods is their versatility and adaptability. BNs can have different functionalities such as predictive analysis and diagnosis, updating and optimization of models, etc. Some recent studies have proposed BN-based frameworks for modeling and assessing the risks of SC [17, 18, 72, 73, 75–77]. Different dependability techniques such as ET, FTA, Hazard and Operability Analysis (HAZOP) and BT diagrams are translated into BNs for risk assessment. In [73] in addition to using FTA in qualitative analysis to identify the causes of risks, they use the fuzzy set theory combined with expert judgement to obtain unknown failure data from basic FTA events. The probability of hazardous events and other related reliability indices occurring is calculated by translating the FTA into a BN model. In [71], they also use a Bayesian approach to make a BT diagram. The proposed approach improves BT diagrams by allowing dynamic analyses. [76] introduced an algorithm also based on BN to map the risks and mitigation measures proposed in SC.

PNs and BNs can consider the multiple states of failure and reparability of components during system behavior modeling, a limitation solved with respect to traditional approaches. However, they have different strengths according to the context. For example, in diagnostic analysis, BN-based approaches make it possible to identify new evidence across the network and update previous beliefs about the probability of failure. When accurate failure data are scarce, expert judgments are often used to obtain the prior probability of BN nodes. There are criticisms of the subjectivity of expert judgement. However, several studies (e.g. [73, 74]) serve to illustrate the effectiveness of BNs in SC modeling and management. BN combines both statistical data and subjective judgments, if data are not available. In this sense, they are considered more robust to other methods, as they can update previous assumptions and probabilities by learning from the new information.

However, the interdependent nature of the elements of the SC should be considered to the greatest extent possible. This is the key aspect of this analysis. In most studies, the proposal only optimizes a portfolio of specific strategies for a single performance measure rather than considering multiple (potentially conflicting) measures. In this regard, we highlight the contribution of [72] to overcoming these constraints through the introduction and implementation of an integrated SCRM approach, which considers the impact of SC risks on multiple objectives and optimizes mitigation strategies. In this way, research remains necessary, not only to capture the interdependencies between risks, but also as a holistic approach to the entire risk management process within an environment of interaction between risks and strategies.

As a summary, a wide and varied range of methods were identified and grouped as shown in Fig. 2. Considering the 107 reviewed papers, there is an increasing trend in the use of integrated approaches. Approximately 40% of the reviewed studies adopt the integration of two or more methods. In general, disruption analysis techniques (85.1%) is the most common type adopted. Among this group, FMEA has been the

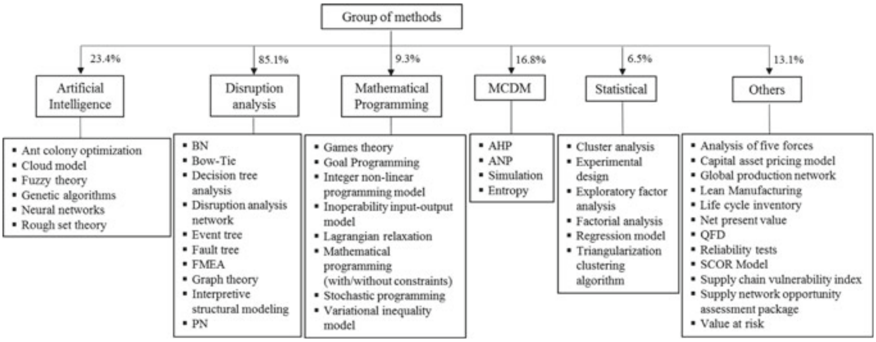

Fig. 2 Groups of identified methods

most used (29%), followed by FTA and BN (11% each one). In the sense of overcoming the limitation of common cause factor modeling within the risk network, the trend toward BNs and PNs approaches is appreciated. These methods are highlighted by their robustness in mitigating many of the limitations of the classical methods.

Due to the highly subjective nature and the lack of information, it is often difficult to quantify risk parameters. In this sense, Artificial Intelligence tools group (23%) show interesting trends. In this group, fuzzy theory (80%) plays a significant role in obtaining more reliable risk assessments in environments under random and epistemic uncertainty.

Integration with MCDM methods is another remarkable combination (13%). Of this group, in particular, the AHP method is highlighted (35.7%). Considering all the 46 different tools identified in the reviewed studies, many of them are used only once (14 out of 46). This is the case of the techniques grouped under the label “Others”, which includes common techniques in SC and business management.

4 Conclusions

This paper presented a literature review of 107 studies that propose qualitative/quantitative, individual/integrated models to support SCRM based on dependency as a key dimension. The results show approximately 40% of the studies presented integrated methods of two or more methods with the aim of obtaining more reliable and effective risk assessments. Disruption analysis tools and Artificial intelligence are the most explored types of methods. FMEA and fuzzy sets are the most common ones combined with others but growing trends toward Bayesian approaches are appreciated.

From the standpoint of effectiveness, BNs, PNs and fuzzy approaches are considered robust approaches to manage dependency combined with ambiguous reasoning in environments under uncertainty. The analysis of common cause disruptive events and the joint impact can lead to better management of SCs rather than treating each risk type in isolation. This can contribute to the optimization of risk strategies due to a holistic management of the process.

Once again, elements of integrative thinking can be appreciated, using the combination of different perspectives to represent and express the risk level more reliably. Interdependencies and uncertainties are relevant issues to effective risk management, therefore integrated methods will continue to play a vital role to SCRM. In many cases, a combination of quantitative and qualitative methods constitute the adequate way to support decision-making.

References

1. Wagner SM, Bode C (2008) An empirical examination of supply chain performance along several dimensions of risk. J Bus Log 29:307–325
2. Christopher M, Mena C, Khan O, Yurt O (2011) Approaches to managing global sourcing risk. Supply Chain Manag Int J 16:67–81
3. Fahimnia B, Tang CS, Davarzani H, Sarkis J (2015) Quantitative models for managing supply chain risks: a review. Eur J Oper Res 247:1–5
4. Aqlan F, Mustafa E (2014) Integrating lean principles and fuzzy bow-tie analysis for risk assessment in chemical industry. J Loss Prev Process Ind 29(1):39–48
5. Tang CS (2006) Perspectives in supply chain risk management. Int J Prod Econ 103(2):451–488
6. Sodhi MS, Son BG, Tang CS (2012) Researchers' perspectives on supply chain risk management. Prod Oper Manag 21:1–3
7. Ho W, Zheng T, Yildiz H, Talluri S (2015) Supply chain risk management: a literature review. Int J Prod Res 53:5031–5069
8. Rajagopal V, Venkatesan SP, Goh M (2017) Decision-making models for supply chain risk mitigation: a review. Comput Ind Eng 113:646–682
9. Tranfield D, Denyer D, Smart P (2003) Towards a methodology for developing evidence-informed management knowledge by means of systematic review. Br J Manag 14(3):207–222
10. Mokhtari K, Ren J, Roberts C, Wang J (2011) Application of a generic bow-tie based risk analysis framework on risk management of sea ports and offshore terminals. J Hazard Mater 192(2):465–475
11. Xia D, Chen B (2011) A comprehensive decision-making model for risk management of supply chain. Exp Syst Appl 38:4957–4966
12. Boateng P, Chen Z, Ogunlana SO (2015) An analytical network process model for risks prioritization in megaprojects. Int J Project Manage 33:1795–1811
13. Lockamy A, McCormack K (2010) Analysing risks in supply networks to facilitate outsourcing decisions. Int J Prod Res 48:593–611
14. Brooker P (2011) Experts, Bayesian Belief Networks, rare events and aviation risk estimates. Saf Sci 49:1142–1155
15. Tan Q, Chen G, Zhang L, Fu J, Li Z (2013) Dynamic accident modeling for high-sulfur natural gas gathering station. Process Saf Environ Prot 92(6):565–576
16. Montewka J, Ehlers S, Goerlandt F, Hinz T, Tabri K, Kujala P (2014) A framework for risk assessment for maritime transportation systems—A case study for open sea collisions involving RoPax vessels. Reliab Eng Syst Safety 124:142–157
17. Qazi A, Quigley J, Dickson A, Ekici SO (2017) Exploring dependency based probabilistic supply chain risk measures for prioritising interdependent risks and strategies. Eur J Oper Res 259:189–204
18. Fakhravara D, Khakzadb N, Reniers G, Cozzani V (2017) Security vulnerability assessment of gas pipelines using Discrete-time Bayesian network. Process Saf Environ Prot 111:714–725

19. Ojha R, Ghadge A, Kumar Tiwari M, Bititci US (2018) Bayesian network modelling for supply chain risk propagation. Int J Prod Res 56,17:5795–5819
20. Chevreau FR, Wybo JL, Cauchois D (2006) Organizing learning processes on risks by using the bow-tie representation. J Hazard Mater 130(3):276–283
21. Tsai MC, Liao CH, Han CS (2008) Risk perception on logistics outsourcing of retail chains: model development and empirical verification in Taiwan. Supply Chain Manag Int J 13:415–424
22. Jacinto C, Silva C (2010) A semi-quantitative assessment of occupational risks using bow-tie representation. Saf Sci 48(8):973–979
23. Markowski A, Kotunia A (2011) Bow-tie model in layer of protection analysis. Process Saf Environ Prot 89(4):205–213
24. Shahiar A, Sadiq R, Tesfamariam S (2012) Risk analysis for oil and gas pipelines: A sustainability assessment approach using fuzzy based bow-tie analysis. J Loss Prev Process Ind 25(3):505–523
25. Ferdous R, Khan F, Sadiq R, Amyotte P, Veitch B (2012) Handling and updating uncertain information in bow-tie analysis. J Loss Prev Process Ind 25(1):8–19
26. Khakzad N, Khan F, Amyotte P (2012) Dynamic risk analysis using bow-tie approach. Reliab Eng Syst Safety 104(1):36–44
27. Berger PD, Gerstenfeld A, Zeng AZ (2004) How many suppliers are best? a decision-analysis approach. Omega 32:9–15
28. Van Delft C, Vial JP (2004) A practical implementation of stochastic programming: An application to the evaluation of option contracts in supply chains. Automatica 40(5):743–756
29. Ruiz-Torres AJ, Mahmoodi F (2007) The optimal number of suppliers considering the costs of individual supplier failures. Omega 35:104–115
30. Yang M, Khan F, Lye L (2013) Precursor-based hierarchical Bayesian approach for rare event frequency estimation: a case of oil spill accidents. Process Saf Environ Prot 91(5):333–342
31. Wu T, Blackhurst J, O'grady P (2007) Methodology for supply chain disruption analysis. Int J Prod Res 45:1665–1682
32. Sinha PR, Whitman LE, Malzahn D (2004) Methodology to mitigate supplier risk in an aerospace supply chain. Supply Chain Manag: Int J 9:154–168
33. Cassanelli G, Mura G, Fantini F, Vanzi M, Plano B (2006) Failure analysis-assisted FMEA. Microelectron Reliab 46(9–11):1795–1799
34. Hu AH, Hsu CW, Kuo TC, Wu WC (2009) Risk evaluation of green components to hazardous substance using FMEA and FAHP. Exp Systh Appl 36(3 PART 2), 7142–7147 (2009).
35. Chin K-S, Wang Y-M, Poon GKK, Yang J-B (2009) Failure mode and effects analysis by data envelopment analysis. Decis Support Syst 48(1):246–256
36. Giannakis M, Louis M (2011) A multiagent based framework for supply chain risk management. J Purchasing Supply Manag 17:23–31
37. Lavastre O, Gunasekaran A, Spalanzani A (2012) Supply chain risk management in French companies. Decis Support Syst 52:828–838
38. Chen P-S, Wu M-T (2013) A modified failure mode and effects analysis method for supplier selection problems in the supply chain risk environment: a case study. Comput Ind Eng 66(4):634–642
39. Jong CH, Tay KM, Lim CP (2013) Application of the fuzzy failure mode and effect analysis methodology to edible bird nest processing. Comput Electron Agriculture 96:90–108
40. Behún M, Kleinová J, Kamaryt T (2014) Risk assessment of non-repetitive production processes. Procedia Eng 69:1281–1285
41. Bradley JR (2014) An improved method for managing catastrophic supply chain disruptions. Bus Horiz 57(4):483–495
42. Kolich M (2014) Using Failure mode and effects analysis to design a comfortable automotive driver seat. Appl Ergon 45(4):1087–1096
43. Jevgeni S, Eduard S, Roman Z (2015) Framework for continuous improvement of production processes and product throughput. Procedia Eng 100:511–519

44. Lindhe A, Rosén L, Norberg T, Bergstedt O (2009) Fault tree analysis for integrated and probabilistic risk analysis of drinking water systems. Water Res 43(6):1641–1653
45. Cigolini R, Rossi T (2010) Managing operational risks along the oil supply chain. Prod Plan Control 21:452–467
46. Curcurù G, Galante GM, La Fata CM (2012) Epistemic uncertainty in fault tree analysis approached by the evidence theory. J Loss Prev Process Ind 25(4):667–676
47. Kumar S, Havey T (2013) Before and after disaster strikes: a relief supply chain decision support framework. Int J Prod Econ 145:613–629
48. Abuswer M, Amyotte P, Khan F, Morrison L (2013) An optimal level of dust explosion risk management: Framework and application. J Loss Prev Process Ind 26(6):1530–1541
49. Zirilli T (2015) Die crack failure mechanism investigations depending on the time of failure. Microelectron Reliab 55(9–10):1600–1606
50. Di Rito G, Schettini F (2016) Impacts of safety on the design of light remotely-piloted helicopter flight control systems. Reliab Eng Syst Safety 149(C):121–129
51. Sherwin MD, Medal H, Lapp SA (2016) Proactive cost-effective identification and mitigation of supply delay risks in a low volume high value supply chain using fault tree analysis. Int J Prod Econ 175:153–163
52. Xiao T, Yang D (2008) Price and service competition of supply chains with risk-averse retailers under demand uncertainty. Int J Prod Econ 114:187–200
53. Xiao T, Yang D (2009) Risk sharing and information revelation mechanism of a one-manufacturer and one-retailer supply chain facing an integrated competitor. Eur J Oper Res 196:1076–1085
54. Li J, Wang S, Cheng TCE (2010) Competition and cooperation in a single-retailer two-supplier supply chain with supply disruption. Int J Prod Econ 124:137–150
55. Khilwani N, Tiwari MK, Sabuncuoglu I (2011) Hybrid petri-nets for modelling and performance evaluation of supply chains. Int J Prod Res 49:4627–4656
56. Faisal MN, Banwet DK, Shankar R (2006) Supply chain risk mitigation: modeling the enablers. Bus Process Manag J 12:535–552
57. Pfohl H-C, Gallus P, Thomas D (2011) Interpretive structural modelling of supply chain risks. Int J Phys Distribut Log Manag 41(9):839–859
58. Diabat A, Govindan K, Panicker VV (2012) Supply Chain risk management and its mitigation in a food industry. Int J Prod Res 50:3039–3050
59. Hung KT, Ryu S (2008) Changing risk preferences in supply chain inventory decisions. Prod Plann Control 19:770–780
60. Laeequddin M, Sardana GD, Sahay BS, Waheed KA, Sahay V (2009) Supply chain partners' trust building process through risk evaluation: the perspectives of UAE packaged food industry. Supply Chain Managemen Int J 14:280–290
61. Skipper JB, Hanna JB (2009) Minimizing supply chain disruption risk through enhanced flexibility. Int J Phys Distribut Log Manag 39:404–427
62. Aloini D, Dulmin R, Mininno V (2012) Risk assessment in ERP projects. Inf Syst 37:183–199
63. Liu L (2018) Liu, X, Liu, G: The risk management of perishable supply chain based on coloured Petri Net modeling. Inf Process Agriculture 5:47–59
64. Ramakrishnan M (2016) Unavailability estimation of shutdown system of a fast reactor by Monte Carlo simulation. Ann Nucl Energy 90:264–274
65. Bugert N, Lasch R (2018) Effectiveness of responsive pricing in the face of supply chain disruptions. Comput Ind Eng 124:304–315
66. Brun AM, Caridi KF, Salama, Ravelli I (2006) Value and risk assessment of supply chain management improvement projects. Int J Prod Econ 99, 186–201 (2006)
67. Hung SJ (2011) Activity-based divergent supply chain planning for competitive advantage in the risky global environment: A DEMATEL-ANP fuzzy goal programming approach. Exp Syst Appl 38:9053–9062
68. Cao J, Song W (2016) Risk assessment of co-creating value with customers: A rough group analytic network process approach. Exp Syst Appl 55:145–156

69. Feng N, Wangb HJ, Minqiang L (2014) A security risk analysis model for information systems: Causal relationships of risk factors and vulnerability propagation analysis. Inf Sci 256:57–73
70. Khakzad N, Khan F, Amyotte P (2013) Dynamic safety analysis of process systems by mapping bow-tie into Bayesian network. Process Saf Environ Prot 91(1):46–53
71. Badreddine A, Ben Amor N (2013) A Bayesian approach to construct bow tie diagrams for risk evaluation. Process Safety Environ Protect 91(3):159–171
72. Qazi A, Dickson A, Quigley J, Gaudenzi B (2018) Supply chain risk network management: A Bayesian belief network and expected utility based approach for managing supply chain risks. Int J Prod Econ 196:24–42
73. Yazdi M, Kabir S (2017) A fuzzy bayesian network approach for risk analysis in process industries. Process Saf Environ Protect 111:507–519 (2017)
74. Yang Z, Bonsall S, Wang J (2008) Fuzzy rule-based Bayesian reasoning approach for prioritization of failures in FMEA. IEEE Trans Reliab 57(3):517–528
75. Wei-Shing W, Chen-Feng Y, Jung-Chuan Ch, Pierre-Alexandre Ch, Yang-Chi Ch (2015) Risk assessment by integrating interpretive structural modeling and Bayesian network, case of offshore pipeline project. Reliab Eng Syst Safety 142:515–524
76. Garvey MD, Carnovale S, Yeniyurt S (2015) An analytical framework for supply network risk propagation: A Bayesian network approach. Eur J Oper Res 243:618–627
77. Wang ZZ, Chen C (2017) Fuzzy comprehensive Bayesian network-based safety risk assessment for metro construction projects. Tunn Undergr Space Technol 70:330–342
78. Ferdous R, Khan F, Sadiq R, Amyotte P, Veitch B (2013) Analyzing system safety and risks under uncertainty using a bow-tie diagram: An innovative approach. Process Saf Environ Prot 91(1–2):1–8
79. Aqlan F, Lam S (2015) A fuzzy-based integrated framework for supply chain risk assessment. Int J Prod Econ 161:54–63
80. Liu Z, Cruz JM (2012) Supply Chain Networks with Corporate Financial Risks and Trade Credits under Economic Uncertainty. Int J Prod Econ 137:55–67
81. Hallikas J, Puumalainen K, Vesterinen T, Virolainen VM (2005) Risk-based Classification of Supplier Relationships. J Purchasing Supply Manag 11:72–82
82. Ruiz-Torres AJ, Mahmoodi F, Zeng AZ (2013) Supplier selection model with contingency planning for supplier failures. Comput Ind Eng 66:374–382
83. Hahn GJ, Kuhn H (2012) Value-based performance and risk management in supply chains: a robust optimization approach. Int J Prod Econ 139:135–144
84. Bidder OR, Arandjelović O, Almutairi F, Shepard ELC, Lambertucci SA, Qasem LA, Wilson RP (2014) A risky business or a safe BET? A Fuzzy Set Event Tree for estimating hazard in biotelemetry studies. Anim Behav 93:143–150
85. Javidi M, Abdolhamidzadeh B, Reniers G, Rashtchian D (2015) A multivariable model for estimation of vapor cloud explosion occurrence possibility based on a Fuzzy logic approach for flammable materials. J Loss Prev Process Ind 33:140–150
86. Elleuch H, Hachicha W, Chabchoub H (2014) A combined approach for supply chain risk management: Description and application to a real hospital pharmaceutical case study. J Risk Res 17:641–663
87. Tuncel G, Alpan G (2010) Risk assessment and management for supply chain networks: a case study. Comput Ind 61:250–259
88. Pujawan IN, Geraldin LH (2009) House of risk: a model for proactive supply chain risk management. Bus Process Manag J 15:953–967
89. Braglia M, Frosolini M, Montanari R (2003) Fuzzy criticality assessment model for failure modes and effects analysis. Int J Q Reliab Manag 20(4):503–524
90. Sharma RK, Kumar D, Kumar P (2005) Systematic failure mode effect analysis (FMEA) using fuzzy linguistic modelling. Int J Q Reliab Manag 22(9):986–1004
91. Tay KM, Lim CP (2006) Fuzzy FMEA with a guided rules reduction system for prioritization of failures. Int J Q Reliab Manag 23(8):1047–1066
92. Liu H-C, Liu L, Bian Q-H, Lin Q-L, Dong N, Xu P-C (2011) Failure mode and effects analysis using fuzzy evidential reasoning approach and grey theory. Expert Syst Appl 38(4):4403–4415

93. Chaudhuri A, Mohanty BK, Singh KN (2013) Supply chain risk assessment during new product development: a group decision making approach using numeric and linguistic data. Int J Prod Res 51:2790–2804
94. Rohmah DUM, Dania WAP, Dewi IA (2015) Risk measurement of supply chain organic rice product using fuzzy failure mode effect analysis in MUTOS Seloliman Trawas Mojokerto. Agriculture Agricultural Sci Procedia 3:108–113
95. Kabir S, Walker M, Papadopoulos Y, Rüde E, Securius P (2016) Fuzzy temporal fault tree analysis of dynamic systems. Int J Approx Reason 77:20–37
96. Sayed HE, Gabbar HA, Miyazaki S (2009) A hybrid statistical genetic-based demand forecasting expert system. Exp Syst Appl 36:11662–11670
97. Niknejad A, Petrovic D (2017) Analysis of impact of uncertainty in global production networks' Parameters. Comput Ind Eng 111:228–238
98. Nakatani J, Tahara K, Nakajima K, Daigo I, Kurishima H, Kudoh Y, Matsubae K, Fukushima Y, Ihara T, Kikuchi Y, Nishijima A, Moriguchi Y (2018) A graph theory-based methodology for vulnerability assessment of supply chains using the life cycle inventory database. Omega 75:165–181
99. Wagner SM, Neshat N (2010) Assessing the vulnerability of supply chains using graph theory. Int J Prod Econ 126:121–129
100. Park S, Lee TE, Sung CS (2010) A three-level supply chain network design model with risk-pooling and lead times. Transp Res Part E: Log Transp Rev 46:563–581
101. Lee C, Lv Y, Hong Z (2013) Risk modelling and assessment for distributed manufacturing system. Int J Prod Res 51(9):2652–2666
102. Blackhurst J, Rungtusanatham J, Scheibe K, Ambulkard S (2018) Supply chain vulnerability assessment: a network based visualization and clustering analysis approach. J Purchasing Supply Manag 24:21–30
103. Guo Y, Meng X, Wang D, Meng T, Liu S, He R (2016) Comprehensive risk evaluation of long-distance oil and gas transportation pipelines using a fuzzy Petri net model. J Nat Gas Sci Eng33:18–29
104. Ho W, Dey PK, Lockström M (2011) Strategic sourcing: a combined QFD and AHP approach in manufacturing. Supply Chain Manag: Int J 16:446–461
105. Zhang K, Chai Y, Yang SX, Weng D (2011) Pre-warning analysis and application in traceability systems for food production supply chains. Exp Syst Appl 38:2500–2507
106. Zsidisin GA, Ellram LM (2003) An agency theory investigation of supply risk management. J Supply Chain Manag 39:15–27
107. Jiang B, Li J, Shen S (2018) Supply chain risk assessment and control of port enterprises: qingdao port as case study. Asian J Ship Log 34(3):198–208
108. Huang HY, Chou YC, Chang S (2009) A dynamic system model for proactive control of dynamic events in full-load states of manufacturing chains. Int J Prod Res 47:2485–2506