Multi-criteria risk classification to enhance complex supply networks performance

Abstract

Management of complex supply networks is a fundamental business topic today. Especially in the presence of many and diverse stakeholders, identifying and assessing those risks having a potential negative impact on the performance of supply processes is of utmost importance and, as a result, implementing focused risk management actions is a current lively field of research. The possibility of supporting Supply Chain Risks Management (SCRM) is herein explored from a Multi-Criteria Decision-Making (MCDM)-based perspective. The sorting method ELimination Et Choix Traduisant la REalité (ELECTRE) TRI is proposed as a structural procedure to classify Supply Chain Risks (SCRs) into proper risk classes expressing priority of intervention so as to ease the implementation of prevention and protection measures. This approach is intended to offer structured management insights by means of an immediate identification of the most highly critical risks in a wide set of previously identified SCRs. A real-world case study in the field of the automotive industry is implemented to show the applicability and usefulness of the approach.

Keywords: Supply Chain Risk, Supply Chain Management, Multi-Criteria Decision-Making, ELECTRE TRI.

1 Introduction and research objectives

Supply Chains (SCs) are complex global networks enabling companies to increase their competitive advantage and flexibility as well as to reduce costs by means of a wide range of possibilities in terms of suppliers selection (Chu et al., 2020). Managing SC networks is an extremely delicate task requiring the integration of suitable models aimed at minimising losses while optimising sustainability, as well as best practices of risk management, by making use of proper computational tools (Mogale et al., 2020). The fundamental part played by SCs as main mechanisms to provide, produce, store, and deliver products to consumers is widely recognised (Garvey and Carnovale, 2020). In this context, Supply Chain Management (SCM) is aimed at optimising the whole set of supply assets and flows (for example financial aspects, information flow, raw materials and finite products) participating in business results (Chopra et al., 2013). The main objective of SCM consists in globally increasing the generated value by simultaneously maximising gains and minimising costs. SCM is considered one of the most important aspects related to the management of complex industrial systems (Chand et al., 2017), since it allows to build strategies for gaining sustainable competitive advantages by reducing costs without compromising customers' satisfaction (Mentzer et al., 2001). To such an aim, effective risk management is essential (Lau et al., 2021) and some previous comprehensive evaluation of all the potential supply chain risks (SCRs) is indispensable to make SCM successful in practice (Moktadir et al., 2020). Complex interactions among all the involved stakeholders such as manufacturers, suppliers and retailers make indeed SCs susceptible to diverse risks (Moktadir et al., 2018) depending on multiple aspects, sometimes conflicting with each other. In this context, a multi-criteria decision-making (MCDM) approach represents an effective support for the stage of SCR assessment. This is related to the formal identification of the most relevant aspects (i.e. criteria) involved in the SCR management (SCRM) discipline, whose importance can be established by means of the help of a panel of experts in the field of interest.

The formal objective of this research consists in identifying within a wider set of SCRs, those having a stronger negative impact on the SCM process by taking into consideration current challenges and circumstances (i.e. world economy conjunctures and conflicts in international relations, COVID-19 constraints, and so on). To this aim, SCRs will be classified into risk classes by applying the sorting MCDM method ELimination Et Choix Traduisant la REalité (ELECTRE) TRI. ELECTRE TRI has been extensively applied in the existing literature to treat similar decision-making problems on supply chain risk management, something that confirms its suitability for the field of reference. However, to the best of the authors' knowledge, it is the first time that the technique is proposed for sorting supply chain risks connected to the sector of the developed case study, that is the automotive industry, into priority classes by means of the set of criteria herein considered, including the strategic impact.

The paper is organised as detailed next. Section 2 presents a literature review on the main topics of research. Section 3 describes the proposed method which will be practically applied to a real-world case study. Practical managerial insights will be discussed and analysed in Section 4. Lastly, section 5 provides the conclusions of the work along with possible future lines of development.

2 Literature review

2.1 Current challenges for Supply Chain Risk Management

Given the primary role of SCM for business, industries have developed several strategies oriented to SC costs reduction and efficiency enhancement by adopting such techniques as Just In Time (JIT) procedures, which have been demonstrated to increase productivity (Ghasimi et al., 2014). As affirmed by Yang et al. (Yang et al., 2021), a JIT supply chain brings uncountable advantages to companies and should be based on the acquisition of customer knowledge to be ideally shared among SC stakeholders. JIT-based strategies can indeed guarantee cost flexibility and reveal to be particularly helpful to capture economies of scale (Kim and Shin, 2019). However, this may lead to higher SC complexity as well as vulnerability to failures, which would be translated into the exposure of companies to the occurrence of several SCRs (Wilding et al., 2012; Trkman et al., 2016) responsible of serious financial losses (Wang et al., 2018; Munir et al., 2020).

As discussed in a previous contribution (Carpitella et al., 2019), implementing strategies aimed at protecting from disruptions is the most important objective to be pursued for effectively managing complex networks (Lian et al., 2012; Awoyemi et al., 2018; Hegde et al., 2017; Kuipers, 2012). Moreover, the adaptation capability of networks should be enhanced with respect to possible variations of initial established conditions, not necessarily facing disruption, but with the objective of increasing communication and information exchange through the network. It is then clear as SCRM represents a key factor for enterprises (Levner and Ptuskin, 2015) aimed at minimising potential losses by developing efficient plans for identifying, assessing, treating and continuously monitoring the main SCRs (Neiger et al., 2009; Xie et al., 2011; Ho et al., 2015). Aiming at facilitating SCRM, companies need to promote intra and inter firm integration (Munir et al., 2020) by establishing reliable collaboration among supply chain partners. Integration enables the circulation of important information about risks and helps SC stakeholders in quickly responding to possible disruptions (Liu and Lee, 2018). Several studies have been undertaken on the topic of SCRM; however, the stage of risks identification is quite hard, and this is somehow due to gaps in the literature (Fan and Stevenson, 2018). In any case, SCRs are difficult to identify in a unique manner mainly because of their complex and multifaceted nature (Sodhi et al., 2012; Ho et al., 2015).

One has to observe as SCRM is nowadays facing huge challenges due to the outbreak of the COVID-19 pandemic. Global economic forces are currently changing global trade landscapes and struggling to manage various kinds of SC perturbation. New policies based on the implementation of rigid health protocols are confirming to be essential for long-term SC sustainability (Karmaker et al., 2020). On the whole, Habib et al. (Habib et al., 2020) state that the way the COVID-19 has halted normal life has no precedent in modern history, and dramatic shocks have been caused to supply chains by economic and societal lockdown. Such an outbreak is undoubtedly having a devastating impact on the global economy (Smialek and Tankersley, 2020) and the possibility of another dangerous financial recession with severe disruptions is expected to negatively impact many SCs for the upcoming months (Haren and Simchi-Levi, 2020).

2.2 Supply Chain Risk assessment

Existing approaches in the literature show as SCR identification and assessment strictly depend on the domain of analysis and on the perspective of the study (Abdel-Basset et al., 2019). Despite risks change from a study to another according to risk categories and the related evaluation criteria, they, however, present similarities (Junaid et al., 2020). Many articles classify risks into two categories: internal SCRs and external SCRs (Abdel-Basset et al., 2019; Junaid et al., 2020). Such authors as Rostamzadeh et al. (Rostamzadeh et al., 2018), Fan and Stevenson (Fan and Stevenson, 2018), Louis and Pagell (Louis and Pagell, 2019) add a third category of SCRs, namely risks internal to firms but external to supply chains. A further SCR category has been recently considered (Munir et al., 2020), generated from relationships with customers.

Risks in supply chain centers mainly refer to disruption of flows, and disruptions happen because of the presence of multiple sources (Norrman and Jansson, 2004) such as regulatory changes, relations with customers and suppliers (Gaudenzi and Borghesi, 2006), issues related to labor and workers (Jiang et al., 2009), logistic providers and forecasting errors (Gaudenzi and Borghesi, 2006), machine breakdown, inventory shortage, IT malfunctioning, natural disasters, terrorist attacks (Thun and Hoenig, 2011), geopolitical risks (Vanalle et al., 2020), environmental problems, health and safety risks (Christopher et al., 2011; Ho et al., 2015), cultural divergences (Altay et al., 2018; Junaid et al., 2020), and so on. In this context, it is also important to highlight the need of developing models for supplier selection and order allocation, as they can provide helpful tools leading towards the implementation of suitable procurement strategies capable to deal with diverse critical risks (Rezaei et al., 2020). A fully integrated strategic approach of risk management is certainly crucial to supply chains and, as underlined in (Creazza et al., 2021), this process has to be promptly and proactively addressed without waiting for actual risk occurrence. Furthermore, as expressed in (Raihan et al., 2021), a rich collection of works focused on supply chain risk management stresses the need of effectively addressing vagueness in industrial supply chains by assessing risks from different perspectives.

A significant aspect to be taken into account in such a field of analysis is indeed represented by uncertainty characterising demand and supply (Merzifonluoglu, 2015).

As we underlined in a previous research (Mzougui et al., 2020), traditional methods of risk assessment as those based on Failure Modes, Effects and Criticality Analysis (FMECA) (Committee et al., 2006) are particularly effective to obtain a general and complete overview of risk management and prevention (Tang and Tomlin, 2008). FMECA-based approaches lead indeed to consistent benefits by carrying out a thorough risk evaluation aimed at globally enhancing SC performance (Curkovic et al., 2013) and quality (Ghadge et al., 2012). FMECA-based procedures have been implemented also as a part of sustainability risk management framework, by means of the identification of major SCRs across three dimensions assumed for sustainability, namely economic, social and environmental aspects (Giannakis and Papadopoulos, 2016).

The stage of SCR identification represents then a fundamental and complex part of the entire SCRM process and complexity, and uncertainty increase when it comes to the next stage of risk SCRs assessing. As previously stated, MCDM methods can be useful to cope with the various analysed difficulties, since they are tools able to handle major barriers in analysing risks (Abdel-Basset et al., 2019).

2.3 Multi-criteria decision-making approaches in supply chain risk management

MCDM methods effectively support a plethora of decision problems, and their crucial role has been widely acknowledged (Kumar et al., 2017a). The final decision depends on various evaluation criteria, that sometimes are mutually dependent and conflicting with each other. MCDM methods have the ability of going towards the solution that satisfies the multiple aspects involved with regard to their mutual importance. MCDM methods are capable of managing both qualitative and quantitative aspects when an evaluation concerning a set of alternatives is required (Mulliner et al., 2016).

The MCDM method most commonly used in the literature to assess and manage SCRs is the Analytic Hierarchy Process (AHP) (Bhutta and Huq, 2002; Gaudenzi and Borghesi, 2006; Schoenherr et al., 2008). However, due to the fact that AHP cannot take into account vagueness and uncertainty affecting input data, the fuzzy AHP (FAHP) has been used in several studies for SCRM (Sahu et al., 2015, 2017; Kumar and Garg, 2017; Radivojević and Gajović, 2014). As demonstrated by such authors as Bharsakade et al. (Bharsakade et al., 2021), this method is particularly effective for planning strategic management practices by transforming qualitative judgments affected by vagueness into quantitative data in a structured way. Other MCDM methods have been combined and proposed for the problem under analysis. Samvedi et al. (Samvedi et al., 2013) integrate AHP and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) for evaluating SCRs. Heidari et al. (Heidari et al., 2018) propose to extend the same approach to a fuzzy environment in order to overcome the limitation of using crisp values. However, the need to take into account the cause-effect relationships among criteria, as well as among SCRs (Govindan et al., 2015), has encouraged researchers to use the fuzzy DEcision MAking Trial and Evaluation Laboratory (DEMATEL) method to handle SCRM. For instance, Muhammad and Cavus (Muhammad and Cavus, 2017) evaluate the relationships bonding twelve criteria with relation to learning management systems. Chang and Cheng (Chang and Cheng, 2011) apply the fuzzy DEMATEL to highlight influential factors in evaluating suppliers.

As one can note, several MCDM methods have been proposed in the existing literature, each one being characterised by specific procedures and objectives. MCDM methods can effectively support in achieving the following objectives (Carpitella et al., 2019): selecting the best solution among various options, ranking alternatives to establish their weights and/or to draw up a list of priorities (Vargas et al., 2017), sorting alternatives into different groups on the basis of their common characteristics (Certa et al., 2016). ELECTRE methods can provide effective results by performing precise analyses over a diverse set of alternatives (Akram et al., 2020) and have been proved capable to deal with complex decision-making problems related to the topic of supply chain risk management (Uddin et al., 2019). In particular, ELECTRE TRI has been applied to various application fields and its main advantage with respect to other ranking-based MCDM methodologies consists in the possibility of sorting alternatives into predefined and ordered classes, on the basis of their common features (Carpitella et al., 2021). This approach is an effective alternative procedure with respect to the traditional ranking that it is possible to achieve by means of other approaches, as it enables to effectively support the analyst (Gonçalves et al., 2021) in identifying which set of supply chain risks may have a critical impact on the general level of performance according to the evaluation of a plethora of criteria (Uddin et al., 2019). This view aims to ease the execution of risk management intervention by promoting a more efficient process of risk assessment (Kumar et al., 2017b). For all these reasons, the ELECTRE TRI technique is herein proposed as a sorting MCDM method to group SCRs into risk classes according to the evaluation of suitable criteria, something that will enable to simultaneously take into account uncertainty affecting input evaluations.

3 Materials and Methods

MCDM methods do not guarantee the achievement of optimal solutions. Final results can be considered as the best trade-off under given conditions, namely the established set of criteria, their mutual importance, the evaluations of alternatives under those criteria and, in the case of ELECTRE TRI, the parameters specifically set for running the technique. Furthermore, it is important to underline as the support of decision-makers expert in the field is crucial and they will have to eventually agree with the final outputs to confirm their validity and feasibility. Dealing with human judgments, MCDM applications are indeed always affected by human subjectivity. However, they allow to derive practical results reflecting valuable managerial experience by means of reliable mathematical tools. As already observed, ELECTRE TRI allows to treat uncertainty of input evaluations even if not in an absolute sense. In the present paper, we propose to lead a sensitivity analysis on some of the most important parameters characterising the methodological approach, in order to represent a wide range of situations.

3.1 The ELECTRE TRI sorting method

ELECTRE TRI is applied by performing two consecutive main stages (Carpitella et al., 2021). The first stage consists in developing outranking relations based on concordance and discordance principles. The defined relations are then exploited during the second stage to sort alternatives to classes, according to their common features. The assignment can be carried out through two different procedures. Before carrying out the application, the following input data have to be organised: set of evaluation criteria B_k, under which alternatives have to be evaluated; criteria weights w_k, expressing mutual importance of criteria; set of reference profiles P_j, each one characterised by specific evaluations under each criterion and defined by two limits p_h and p_{h+1}; set of classes C_h identified by reference profiles; set of alternatives A_i with the related evaluations $B_k(A_i)$ assumed under each criterion; a threshold value λ comprised between 0.5 and 1, known as *cutting level* and needed to complete the first stage of ELECTRE TRI; values of indifference, strong preference and veto thresholds, namely I_k, S_k, and V_k, related to the outranking relations. I_k represents the minimal difference to declare preference between a pair of elements, S_k is the minimal difference to declare strong preference between a pair elements, and V_k is the minimal difference highlighting a relation of incompatibility between a pair of elements (Carpitella et al., 2018).

The first stage consists in establishing an outranking relation comparing each alternative with limits of classes, that is with the reference profiles. The following main steps have to be implemented consecutively.

- Calculating partial concordance indices for each criterion. Each alternative A_i is pairwise compared with the defined reference profiles P_j, and concordance indices, noted as $C_k(A_i, P_j)$, are calculated for each criterion B_k by using formula (1).

$$C_k(A_i, P_j) = \begin{cases} 1 \quad if \quad [B_k(P_j) - B_k(A_i)] \leq I_k \\ 0 \quad if \quad [B_k(P_j) - B_k(A_i)] \geq S_k. \\ \frac{B_k(A_i) - B_k(P_j) + S_k}{S_k - I_k} \quad \text{otherwise} \end{cases} \tag{1}$$

  The aggregated concordance index $C(A_i, P_j)$ are then derived by aggregating and weighting the concordance indices for each criterion in the following way:

$$C(A_i, P_j) = \frac{\sum_{k=1}^{K} w_k \cdot C_k(A_i, P_j)}{\sum_{k=1}^{K} w_k}. \tag{2}$$

- Calculating partial discordance indices for each criterion by using (3).

$$D_k(A_i, P_j) = \begin{cases} 1 \quad if \quad [B_k(P_j) - B_k(A_i)] > V_k \\ 0 \quad if \quad [B_k(P_j) - B_k(A_i)] \leq S_k. \\ \frac{B_k(P_j) - B_k(A_i) - S_k}{V_k - S_k} \quad \text{otherwise} \end{cases} \tag{3}$$

- Calculating outranking credibility indices through formula (4).

$$\delta(A_i, P_j) = C(A_i, P_j) \cdot \frac{\prod_{k \in K^*}(1 - D_k(A_i, P_j))}{1 - C(A_i, P_j)}, \tag{4}$$

  K^* being the subset of criteria for which $D_k(A_i, P_j) > C(A_i, P_j)$. When the veto threshold is not established, the credibility index $\delta(A_i, P_j)$ is assumed as equal to the aggregated concordance index $C(A_i, P_j)$.

- Exploiting the specific kind of outranking relation by using the cutting level λ. Specifically, λ represents the threshold value for $\delta(A_i, P_j)$ to accept the hypothesis that A_i outranks P_j. The value of λ is comprised between 0.5 and 1 and should be greater than the quantity equal to $1-$(*highest weight/total weigh*) (Merad et al., 2004; Liu and Ming, 2019). The framework to establish outranking relations is shown in Figure 1, in which ***R***, ***S*** and ***I*** respectively express incompatibility, preference and indifference relations.

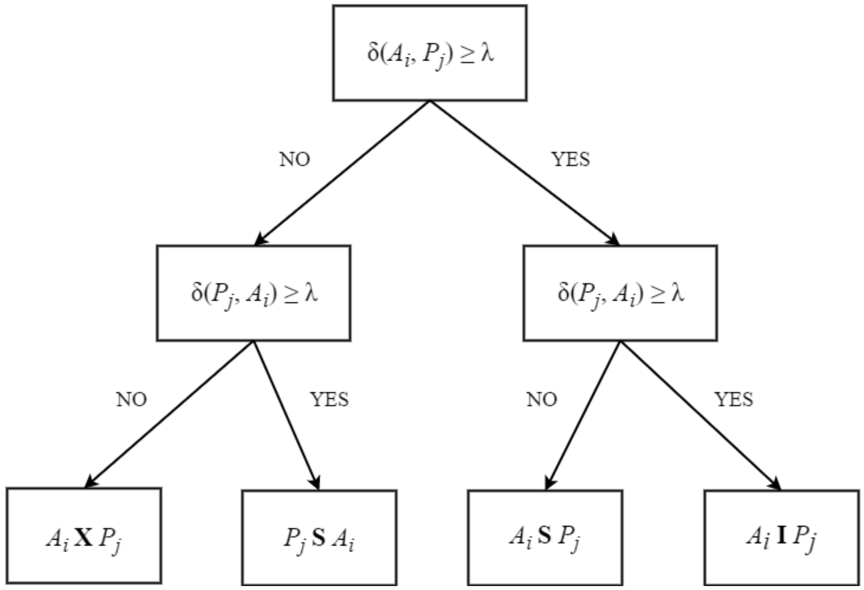

Fig. 1. Framework to establish outranking relations

The second stage consists in assigning alternatives to classes by means of two possible procedures, that are the pessimistic and the optimistic rules, described in the following. In general, the pessimistic procedure has to be preferred to the optimistic rule, tending to assign alternatives to classes defined by a lower profile, this way guaranteeing the achievement of more conservative results. According to the pessimistic (or conjunctive) procedure, alternative A_i is assigned to the class C_h for which the condition that A_i $\boldsymbol{S}$ P_j is verified. The procedure is made of two steps: 1) comparing successively each alternative with the limits of classes: A_i is successively compared to the profiles defining the classes until condition A_i $\boldsymbol{S}$ P_j is verified; 2) assigning alternative A_i to class C_{h+1}. According to the optimistic (or disjunctive) procedure, alternative A_i is assigned to the class C_h for which the condition that P_j $\boldsymbol{S}$ A_i is verified. The procedure is made of two steps: 1) comparing successively each alternative with the limits of classes: A_i is successively compared to profiles defining classes until condition P_j $\boldsymbol{S}$ A_i is verified; 2) assigning alternative A_i to class C_h.

3.2 Real-world case study: presentation and application

The present case study refers to a company operating in the sector of the automotive industry. The choice of this sector is justified by the fact that, as expressed by (Kumar et al., 2021), it has been facing many complex challenges connected to unpredictable demand evolution, rigid legislation, quick technological updates, as well as changes in global mobility patterns. Our aim is to sort alternatives belonging to a set of twenty-three SCRs (A_i, $i = 1, \ldots, 23$) into four ordered risk classes (C_1=D, C_2=C, C_3=B and C_4=A) expressing priority of intervention. Classes have been ordered from class D to class A to express the transition from a condition of low priority to a condition of high priority of intervention in terms of risk prevention/mitigation. These classes highlight the global priority required to manage SCRs according to specific intervals of values assumed by the chosen criteria. The following evaluation criteria are considered: B_1, occurrence; B_2, dependence; B_3, cost; B_4, strategic impact. SCRs have been evaluated under each criterion by involving a decision-making group, and their evaluations have been translated into numerical values ranged within the interval [1, 5]. Figure 2 shows the four ordered classes delimited by three reference profiles with relation to the three evaluation criteria.

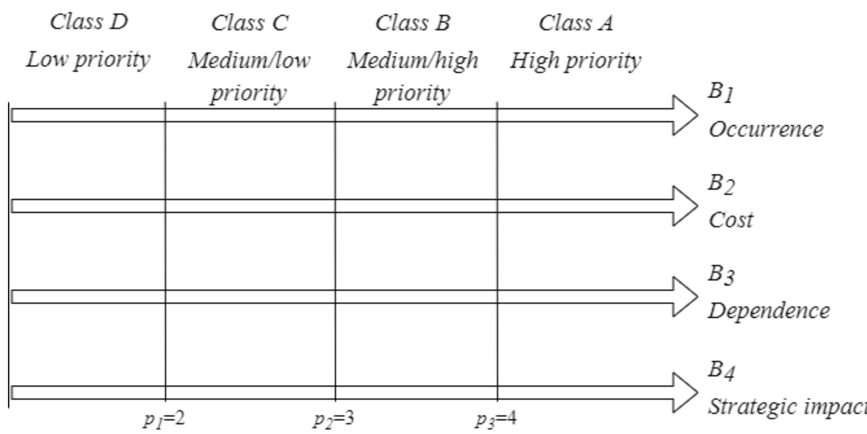

Fig. 2. Classes and profiles over evaluation criteria

The input evaluations, available from the previous research (Mzougui et al., 2020), are synthesised in Table 1. We herein recall the obtained vector of criteria weights **w**=[0.0679, 0.3899, 0.3899, 0.1523]. However, we specify that, instead of ranking risks, we are now interested in sorting them into classes by means of ELECTRE TRI as a structured methodology easily dealing with big numbers of alternatives. In these types of situations, indeed, relying on the possibility of sorting risks into priority classes, instead of obtaining a plain ranking, can be useful to immediately highlight those sets of risks in need of urgent improvement. Also, the nature of this need can be easily distinguished on the basis of common characteristics.

As underlined by Mousseau et al. (Mousseau et al., 2000), threshold values have to be fixed by the decision-maker to properly set the methodology according to the specific requirements of study. Larger values can be first attributed to thresholds and then progressively reduced until considered appropriate for each criterion. The preference and indifference thresholds have been herein assumed as a half and a quarter of the width of the classes (i.e. respectively equal to 0.5 and 0.25), whereas veto threshold as equal to the width of the classes (i.e. equal to 1). Results obtained by means of the pessimistic and optimistic rules are

Table 1. Input data for the ELECTRE TRI application

SCR	Risk description	B_1	B_2	B_3	B_4
R_1	Improper raw materials	4.60	2.00	4.20	3.80
R_2	Sudden design changes	2.80	1.00	3.60	2.80
R_3	Information exchange	2.40	3.00	3.00	3.60
R_4	Requirement accomplishment	2.80	5.00	2.80	3.40
R_5	Ineffective transport	3.40	4.00	3.80	3.40
R_6	Transport network lengthening	2.60	3.00	3.20	3.40
R_7	Taxes increase	2.60	1.00	3.40	4.00
R_8	Raw material market prices increase	3.20	2.00	3.80	3.20
R_9	Equipment or production facilities breakdown	2.00	3.00	3.80	2.80
R_{10}	Production performance	2.80	4.00	3.80	3.00
R_{11}	Human resource (HR) attitude	2.40	2.00	3.60	3.60
R_{12}	Insufficient manufacturing capacity or capability	2.60	4.00	3.20	3.00
R_{13}	Labor and production costs increase	2.20	2.00	4.00	4.00
R_{14}	Production breakdown	3.00	2.00	3.20	3.40
R_{15}	Production disruption	2.40	3.00	3.20	4.00
R_{16}	Matching supplier requirements	3.00	2.00	3.00	3.00
R_{17}	Facilities, HR, policies and processes breakdown	2.40	5.00	3.20	3.80
R_{18}	Inadequate reconfiguration of manufacturing processes	2.60	4.00	3.40	3.40
R_{19}	Inefficient delivery of products	3.00	3.00	4.00	3.80
R_{20}	Supply chain disruptions due to natural disasters	2.20	5.00	4.20	3.60
R_{21}	Supply chain disruptions due to events of terrorism	1.60	1.00	3.20	4.00
R_{22}	Social unrest in region where the supply chain operates	2.00	2.00	3.20	4.20
R_{23}	Dependence on suppliers	2.80	2.00	3.80	4.20

respectively shown in Tables 2a, 2b. The assignment of each SCR to the defined classes has been achieved by varying the cutting level λ within the range [0.5, 1].

Table 2. Assignment of SCRs to classes by means of ELECTRE TRI

(a) Pessimistic procedure

SCR/ λ	0.50	0.60	0.70	0.80	0.90	1.00
R_1	C	C	C	C	C	C
R_2	D	D	D	D	D	D
R_3	B	B	B	B	B	C
R_4	B	B	B	B	B	B
R_5	A	A	A	B	B	B
R_6	B	B	B	B	B	C
R_7	D	D	D	D	D	D
R_8	C	C	C	C	C	C
R_9	C	C	C	C	C	C
R_{10}	B	B	B	B	B	B
R_{11}	C	C	C	C	C	C
R_{12}	B	B	B	B	B	C
R_{13}	C	C	C	C	C	C
R_{14}	C	C	C	C	C	C
R_{15}	B	B	B	B	B	C
R_{16}	C	C	C	C	C	C
R_{17}	B	B	B	B	B	C
R_{18}	B	B	B	B	B	C
R_{19}	B	B	B	B	B	B
R_{20}	B	B	B	B	B	C
R_{21}	D	D	D	D	D	D
R_{22}	C	C	C	C	C	C
R_{23}	C	C	C	C	C	C

(b) Optimistic procedure

SCR/ λ	0.50	0.60	0.70	0.80	0.90	1.00
R_1	B	B	B	B	B	A
R_2	C	C	B	B	B	B
R_3	B	B	B	B	B	B
R_4	A	A	A	A	A	A
R_5	A	A	A	B	B	B
R_6	B	B	B	B	B	B
R_7	B	B	B	B	B	B
R_8	C	C	B	B	B	B
R_9	C	C	B	B	B	B
R_{10}	B	B	B	B	B	B
R_{11}	B	B	B	B	B	B
R_{12}	B	B	B	B	B	B
R_{13}	B	B	B	B	B	B
R_{14}	C	C	C	C	C	B
R_{15}	B	B	B	B	B	C
R_{16}	C	C	C	C	C	C
R_{17}	A	A	A	A	A	A
R_{18}	B	B	B	B	B	B
R_{19}	B	B	B	B	B	B
R_{20}	A	A	A	A	A	A
R_{21}	B	B	B	B	B	B
R_{22}	B	B	B	B	B	B
R_{23}	B	B	B	B	B	B

As previously discussed, the pessimistic procedure is in general preferred to the optimistic procedure, because it tends to assign alternatives to classes defined by a lower profile. In this sense, the pessimistic procedure is considered more conservative. However, in the present case study, the most cautious attitude consists in assigning SCRs to classes defined by higher profiles, the last ones highlighting a need of high priority of intervention. For example, we can observe as SCR R_1 (improper raw materials) is assigned to class C (medium-low priority) by the pessimistic rule and to class A (high priority) by the optimistic rule. In this case, dealing with risk management, we prefer the procedure that do not underestimate the possible impact of a given risk. This is the main reason why, according to the semantic meaning of classes, we prefer adopting the results derived through the optimistic procedure.

For the sake of completeness, aiming at studying the influence of the thresholds on the final assignment, Table 3 shows results derived by the adopted optimistic procedure by varying the veto threshold. Specifically, with respect to the application of Table 2, more strict and less strict conditions have been represented. First, tables 3a 3b respectively show results obtained by fixing a veto threshold respectively equal to 0.5 and 0.75 times the width of the classes. Then, tables 3c and 3d, respectively, show results obtained by fixing a veto threshold respectively equal to 1.25 and 1.5 times the width of the classes. In the four cases, values assumed by indifference and preference thresholds have been modified accordingly.

By observing the results in Table 3, one can note that larger values of the veto thresholds globally lead to assign SCRs to classes characterised by lower priority of intervention. On the contrary, lower values of the veto thresholds lead to assign SCRs to higher classes.

4 Discussion of results and implications for management

Various practical considerations and useful management implications may be derived by analysing the obtained results. The first observation is related to the robustness of results by varying the cutting level. The cutting level λ indicates whether the credibility degree of the analysed outranking relations is sufficiently enough to establish an outranking conclusion regarding the comparison between an alternative and a reference profile (Rocha and Dias, 2008). λ may be interpreted as the required majority of criteria weights in favor of a specific outranking needed to accept that conclusion. We can appreciate as, by progressively increasing the value of λ within the interval [0.5, 1], the pessimistic procedure tends to assign SCRs to lower priority classes whereas, on the contrary, the optimistic procedure tends to assign SCRs to higher priority classes. In any case, we can observe as there are some SCRs assigned to the same class independently on the value

Table 3. Analysing the influence of thresholds on the final assignment (optimistic procedure)

(a) V_k equal to 0.5 times the width of classes

SCR/ λ	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**	**1.00**
R_1	A	A	A	A	A	A
R_2	B	B	B	B	B	B
R_3	B	B	B	B	B	B
R_4	A	A	A	A	A	A
R_5	B	B	B	B	B	B
R_6	B	B	B	B	B	B
R_7	B	B	B	B	B	B
R_8	B	B	B	B	B	B
R_9	B	B	B	B	B	B
R_{10}	B	B	B	B	B	B
R_{11}	B	B	B	B	B	B
R_{12}	B	B	B	B	B	B
R_{13}	B	B	B	B	B	B
R_{14}	C	C	B	B	B	B
R_{15}	B	B	B	B	B	B
R_{16}	C	C	C	C	C	C
R_{17}	A	A	A	A	A	A
R_{18}	B	B	B	B	B	B
R_{19}	B	B	B	B	B	B
R_{20}	A	A	A	A	A	A
R_{21}	B	B	B	B	B	B
R_{22}	B	B	B	B	B	B
R_{23}	A	A	A	A	A	A

(b) V_k equal to 0.75 times the width of classes

SCR/ λ	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**	**1.00**
R_1	B	B	B	B	B	A
R_2	C	C	B	B	B	B
R_3	B	B	B	B	B	B
R_4	A	A	A	A	A	A
R_5	A	A	A	B	B	B
R_6	B	B	B	B	B	B
R_7	B	B	B	B	B	B
R_8	B	B	B	B	B	B
R_9	B	B	B	B	B	B
R_{10}	B	B	B	B	B	B
R_{11}	B	B	B	B	B	B
R_{12}	B	B	B	B	B	B
R_{13}	B	B	B	B	B	B
R_{14}	C	C	C	C	B	B
R_{15}	B	B	B	B	B	B
R_{16}	C	C	C	C	C	C
R_{17}	A	A	A	A	A	A
R_{18}	B	B	B	B	B	B
R_{19}	B	B	B	B	B	B
R_{20}	A	A	A	A	A	A
R_{21}	B	B	B	B	B	B
R_{22}	B	B	B	B	B	A
R_{23}	B	B	B	B	B	A

(c) V_k equal to 1.25 times the width of classes

SCR/ λ	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**	**1.00**
R_1	B	B	B	B	B	A
R_2	C	C	B	B	B	B
R_3	B	B	B	B	B	B
R_4	A	A	A	A	A	A
R_5	A	A	A	B	B	B
R_6	B	B	B	B	B	B
R_7	C	C	C	B	B	B
R_8	B	B	B	B	B	B
R_9	B	B	B	B	B	B
R_{10}	B	B	B	B	B	B
R_{11}	C	B	B	B	B	B
R_{12}	B	B	B	B	B	B
R_{13}	B	B	B	B	B	B
R_{14}	B	B	C	C	C	B
R_{15}	B	B	B	B	B	B
R_{16}	B	B	C	C	C	C
R_{17}	B	B	A	A	A	A
R_{18}	B	B	B	B	B	B
R_{19}	B	B	B	B	B	B
R_{20}	B	B	A	A	A	A
R_{21}	C	C	C	C	B	B
R_{22}	B	B	B	B	B	B
R_{23}	B	B	B	B	B	B

(d) V_k equal to 1.5 times the width of classes

SCR/ λ	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**	**1.00**
R_1	B	B	B	B	B	A
R_2	C	C	C	B	B	B
R_3	B	B	B	B	B	B
R_4	B	B	A	A	A	A
R_5	A	A	A	A	B	B
R_6	B	B	B	B	B	B
R_7	C	C	C	C	B	B
R_8	B	B	B	B	B	B
R_9	B	B	B	B	B	B
R_{10}	A	A	A	B	B	B
R_{11}	B	C	B	B	B	B
R_{12}	B	B	B	B	B	B
R_{13}	B	B	B	B	B	B
R_{14}	B	B	C	C	C	B
R_{15}	B	B	B	B	B	B
R_{16}	B	B	C	C	C	C
R_{17}	B	B	A	A	A	A
R_{18}	B	B	B	B	B	B
R_{19}	B	B	B	B	B	B
R_{20}	B	B	A	A	A	A
R_{21}	C	C	C	C	B	B
R_{22}	B	C	C	C	B	B
R_{23}	B	B	B	B	B	B

assumed by the cutting level. This is, for the example, the case of R_{19} (inefficient delivery of products), which is always assigned to class B (medium-high priority risk) for any value of λ and also by varying the indifference, preference and veto thresholds.

Results obtained via the chosen optimistic procedure (Table 2b) underline as certain SCRs definitely need to be managed with priority, being consistently assigned to class A. This is the case of R_4 (requirement accomplishment), R_{17} (facilities, HR, policies and processes breakdown) and R_{20} (supply chain disruptions due to natural disasters). Proper mitigation and/or preventive interventions should be aimed at reducing the evaluation of criteria given in Table 1, with special regard to those criteria which have associated higher weights. For example, in the case of R_{17}, proper measures should aim to reduce the dependence with other SCRs by separating processes and resources, but also such aspects as the strategic impact and the cost derived by the risk occurrence. To make another example, risks R_{20} (supply chain disruptions due to natural disasters) and R_4 (requirement accomplishment) reveal to be particular important in present times afflicted by the COVID-19 outbreak. The impact of such risks can be reduced by implementing, for instance, efficient strategies of supplier selection to limit the possibility of production breakdown then an excessive cost exposure. This topic will be the objective of further research. Among the risks assigned to class B (medium-high priority), we can observe as R_1 is upgraded to class A when the cutting level is maximum. It means that it has associated a higher criteria evaluation (the associated cost evaluation is indeed quite high) with respect to the other SCRs assigned to class B; this is the reason why, after dealing with the risks assigned to class A, major priority should be given to R_1 within class B. When it comes to the risks assigned to the class C (medium-low priority), results tell us that R_{14} (production breakdown) and R_{16} (matching supplier requirements) are the less urgent. Management interventions for these risks can be postponed.

Regarding significant differences with our previous work (Mzougui et al., 2020), the topics are certainly interconnected but treated from different perspectives and by means of different methodological approaches. Instead of merely ranking supply chain risks, ELECTRE TRI proceeds by sorting these risks into classes expressing priority of intervention according to the considered set of evaluation criteria and their assigned weights. This procedure permits to support the company management in identifying which set of supply chain risks, among those formalised through a previous stage of risk identification, has a stronger influence on system functioning on the basis of the classes in which those risks will be sorted by the mentioned MCDM.

The present application hence represents a further step from the previous risk ranking for an effective SCR management in the field of automotive industry inspired by the philosophy of continuous improvement. We have also showed as, with respect to the SCRs ranking, the assignment to ordered priority classes carried out by means of the sorting procedure ELECTRE TRI offers more structured management insights. This application makes it easier the immediate identification of the highly critical risks belonging to a wider SCR set, so that implementing more focused risk management actions can be possible.

5 Conclusions and future works

The present paper deals with the topic of complex supply network management and, in particular, with the SCRM, which has paramount importance in business. We specifically propose a structured MCDM approach making use of the sorting technique ELECTRE TRI to assign SCRs to ordered classes on the basis of their required priority of intervention, and to move forward with respect to the process of SCRs ranking. When risks are assigned to classes, it can be much easier to immediately identify which aspects require immediate interventions aimed at optimising risk management. The approach is applied to a real-world case study in the field of the automotive industry and various scenarios of analysis have been explored to confirm the robustness of results. The procedure carried out in the present paper is perfectly suitable to deal with those situations in which the number of SCRs to be taken into account is huge.

Possible future developments of the present research may refer to the implementation of a structured framework capable of easing the selection of the best supplier/s on the basis of specific risk requirements.

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