Improved Industrial Risk Analysis via a Human Factor-Driven Bayesian Network Approach

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Abstract This paper develops the traditional Failure Modes, Effects and Criticality Analysis (FMECA) for quantitative risk assessment from a Bayesian Network (BN)-based perspective. The main purpose consists in endowing FMECA with a framework for analysing causal relationships for risk evaluation and deriving probabilistic relations between significant risk factors, which are represented by linguistic variables. The idea is to take advantage of BNs' ability for inference incorporating uncertainty, and thus to enable analysts to obtain valuable information for risk assessment to support such crucial decision-making processes as planning, operation, maintenance, etc. in industry. The proposed framework includes the human factor as a key element of analysis in FMECA-based risk assessment. We propose to consider a new parameter with respect to those traditionally used for the Risk Priority Number (RPN) calculation, namely the human factor, something that existing approaches scarcely consider in the current practice. The contributions to the risk function calculation of the identified factors are determined using a Multi-criteria Decision-Making (MCDM) perspective. We present and develop a real-world application in the alimentary industry on supply chain risk (SCR) management, a fundamental business topic where risk and supply chain management processes merge.

Keywords Discrete mathematical modelling · Human factor · Risk management · Optimisation · Bayesian networks · Supply chain risk

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Notation table

Notation	Definition
SCR	Supply Chain Risk
RPN	Risk Priority Number
S	Severity
O	Occurrence
D	Detection
H	Human Factor
R	Global risk value, calculated as $R = \mathrm{int}[S^{w_S} \times O^{w_O} \times H^{w_H}]$
$\mathrm{Ind}(A_i; \mathrm{NoDesc}(A_i) \vert \mathrm{Pa}(A_i))$	Relations of conditional independence (Ind) of a (generic) node A_i with respect to its non-descendants (NoDesc) given the values of its parents (Pa)
$P(A_1, \ldots, A_n)$	Joint probability distribution given the conditional probability tables, defined as $P(A_1, \ldots, A_n) = \prod_{i=1}^{n} P(A_i \vert \mathrm{Pa}(A_i))$
$\mathbf{P}(\mathbf{X} \vert \mathbf{e})$	Vector probability of variables in vector $\mathbf{X}$, given the vector evidence $\mathbf{e}$, determined as $\mathbf{P}(\mathbf{X} \vert \mathbf{e}) = \alpha \mathbf{P}(\mathbf{X}, \mathbf{e}) = \alpha \sum_{\mathbf{y}} \mathbf{P}(\mathbf{X}, \mathbf{e}, \mathbf{y})$, being α a normalizing factor, and $\mathbf{Y}$ hidden variables

1 Introduction and Literature Review

The concept of risk permeates human daily life at virtually any level. When it comes to business, any risk management process has to be organised and implemented on the basis of the specific sector of activity. In any case, the primary objective of this process has to be the maximisation of safety and security conditions for human resources, along with the optimisation of such criteria as time effectiveness, production and services' quality, and economic aspects. Considering the utmost importance of risk-oriented management [62], good results can be achieved by accurately leading the stages of hazard identification and risk assessment [20]. On the whole, despite its crucial importance, risk management processes are still carried out on the basis of too simplistic evaluations approaches, even in those business sectors where safety and security are imperative requirements [26]. This is the reason why various authors agree about the fact that novel decision-making frameworks have to be developed and implemented for risk management [39, 46], above all when managing epistemic uncertainty affecting data is necessary to achieve more precise evaluations [40].

Risks are traditionally assessed on the basis of qualitative and/or quantitative evaluations attributed to previously identified parameters. These parameters (i.e. risk factors) basically refer to the associated frequency of risk occurrence and to the so-called magnitude of severity, the latter representing a measure of the potential negative impact on people and systems if a given risk occurs. In this context, since humans are intrinsically related to risks of diverse nature, integrating the human factor as a parameter for risk evaluation can be strategic. It is indeed unarguable that human resources constitute the focal point of any business field [10]. Moreover, people acquiring new awareness and capabilities about risk management processes can have a tremendous influence in making business successful. As a result, efforts in developing mathematical models for human factors analysis have been oriented to cope with the natural discontinuity between humans and systems features [7].

Traditional risk assessment approaches performed by Failure Modes, Effects and Criticality Analysis (FMECA) are developed on the basis of inductive reasoning procedures aimed at defining, identifying and quantitatively evaluating potential failure modes involving complex systems [2], as well as individual components [18]. FMECA is considered a valuable tool to comprehensively collect and organise experts' knowledge with the purpose of quantifying those risks related to systems' usage [15]. FMECA-based analyses play an important part in highlighting critical components and increasing efficiency of core processes [22]. By means of an early identification of root causes [58], FMECA outputs are indeed useful to proceed towards the implementation of suitable prevention and/or mitigation measures [21], then to contribute to global systems' states improvement [16]. However, FMECA is characterised by various shortcomings [3], for which previous assumptions and clarifications should be made [19]. First of all, the considered risk factors are commonly assessed without taking into account the existence of dependencies among them [41], something that may lead to imprecise results with the consequent adoption of ineffective decisions. This is one of the aspects we aim to improve by proposing a multi-criteria evaluation approach capable to deal with the existence of relations of dependence among the parameters relevant to the analysis. Another reason why traditional FMECA analyses have been widely criticized in the literature [14, 31, 32, 34, 35, 64] consists in not considering the different importance of the involved parameters, i.e. different weights in evaluating risks. Also in this case, we are going to deal with such a shortcoming by including the possibility of attributing different degrees of importance to these parameters. In addition, such important aspects as human factors in terms of human contributions to risk are not properly taken into account, despite being fundamental for organisational effectiveness and safety [11]. This is the main reason why the present research aims to embody such an aspect within the risk function calculation. Apart from all the mentioned weaknesses, FMECA also lacks of the possibility of providing accurate analyses of causal relationships for risk assessment, and this can be resolved by endowing it with a Bayesian Network (BN) framework [9], which will allow to derive probabilistic inference among the most significant parameters under study. As affirmed in [1], BN applications are beneficial for implementing effective reliability models and decision support systems under uncertainty conditions. Furthermore, BNs have been recently and successfully adopted for real-time risk assessment [1, 30], also in the presence of decision-making groups [56], contributing to establish effective decision-making strategies for risk management [53].

As an extension of a previous contribution [12], this research develops the traditional FMECA [25] for quantitative risk analysis from a BN-based perspective, which reveals to be useful to make more accurate predictions about parameters' values. With respect to the previous conference paper, as we are going to explain next more in detail, the present research deeply explores and updates traditional FMECA parameters and makes use of Multi-criteria Decision-Making (MCDM) along with BNs as an additional integration to risk analysis processes. This may ease the discrimination among the relative importance attributed to the different assessment parameters. Moreover, we have considerably extended the practical case study, which includes data from various real companies operating within the alimentary industry, in order to get comprehensive results that may be significant for the whole sector. More in detail, the main purpose of the present research consists in providing a framework for analysing causal relationships for risk evaluation and deriving probabilistic relations between significant risk factors. These parameters, evaluated by means of linguistic variables, include the human factor as a key element of analysis. Embodying the human contribution to the risk function within the process of risk management provides an effective perspective, as human factors have been recognised among the primary sources of potential accidents [63]. For this reason, we integrate the fields of human factors management and risk management with the aim to design successful strategies and promote best practices [27] capable to increase business performance. As already said, a MCDM perspective is herein proposed to take into account the different mutual importance of risk factors (i.e. criteria) and their different contribution to the risk function calculation according to the influence of significant sub-criteria. The usefulness of MCDM methods in the risk analysis field is supported by the existing literature [57], in particular, to enhance FMECA-based approaches effectiveness [33]. For instance, a MCDM-based approach making use of several methods is proposed in [8] to increase the whole reliability of FMECA results by eventually presenting a benchmark FMECA example for a process plant gearbox. The authors present a review on recent MCDM applications in FMECA case studies, highlighting the useful role of these methods in supporting failure modes prioritisation. MCDM models have been indeed widely suggested for enhancing the robustness of the final ranking of risks [17] by specifically integrating subjective and objective weights of group members as well as relevant factors [59]. The field of supply chain management has been explored with relation to the treated topic, see [37], among others. The authors propose a MCDM integration aimed at assessing risks and proposing strategic solutions to face the impact of COVID-19 on organisational efficiency. Specifically, they underline the role of the Analytic Network Process (ANP) as a technique capable to deal with dependence bounding the main factors of analysis. In such a direction, upon formalising the parameters to be used for the risk function calculation, the application of the ANP is herein suggested to calculate their related weights by simultaneously taking into account relationships of dependence bounding the main decision-making elements of analysis. Attributing different weights to the risk parameters would indeed enable us to consider their diverse contribution to the final risk score.

The proposed theoretical approach is applied to a real-world use case on supply chain risk (SCR) management in the industrial alimentary sector. The choice of this topic, which currently represents a lively research area, is further motivated by the fact that FMECA has been recently extended to supply chain risk evaluation [41]. Over the last years, researchers have been developing new models and/or integrating existing methods with the purpose of minimising the occurrence of operational risks while simultaneously managing supply chain operational risks [44]. Effective management is particularly crucial in the alimentary industry, given the fact that products may have perishable characteristics and their quality could be inexorably compromised by inefficiencies affecting supply chains [45]. As underlined in [5], designing and timely implementing suitable prevention and/or mitigation actions is fundamental to control the effects of supply chain disruptions. This is the reason why the literature shows as firms have made considerable efforts to identify and apply suitable resilience strategies. As developing supply chain resilience becomes crucial to businesses, reliable theoretical models should be developed to first evaluate the effects of supply chain disruptions on performance outcomes [61].

The connection between practical world problems and theoretical research is always a challenging domain. As discussed, for example, in [38], the translation from a mathematical model to an application is sometimes a difficult transit as models are not comprehensible to common users without mathematical background. In the mentioned article the authors propose extracting rules from mathematical models and presenting only extracted rules to the final user. The related process of data collection has been carried out in the literature by using expert knowledge and management input, as in [49]. Another way to extract useful data is discussed, for example, in [28]. This topic is further detailed in [6], where the authors elaborate about the possibility of making use of such tools as BNs and fuzzy systems. In the present case, the practical use of SCR assessment models is linked to the proposed theory by including the human factor as a significant parameter. In this way, the contribution of decision support systems to real-world logistic scenarios will be possible. Our approach aims to be of practical use for companies in their supply chain operations, even though it can also be extended to other sectors of activity.

With this recognition, the use case herein presented involves four companies of the alimentary manufacturing industry. Extensive sessions of brainstorming have been led and many surveys have been carried out in collaboration with a decision-making group of sixty stakeholders, who have been grouped according to their specific roles. This study provides meaningful insights for successful SCR assessment in the analysed industrial sector. Best practices and procedures can be derived and adopted by logistic managers to pursue process automation and operational efficiency.

The paper is organised as follows. The proposed approach in terms of methodologies and main novelties is presented in the next Sect. 2. The application on SCR management focused on the field of alimentary industry is developed in Sect. 3, along with the discussion of final results and their practical implications. Conclusions and possible future developments of the present research are lastly outlined in Sect. 4.

2 The Proposed Approach

The research objectives of the present paper are further formalised as follows:

- to review the risk parameters used in traditional FMECA and embodying the human factor into the risk function calculation, what constitutes a new perspective in the field of risk analysis;
- to calculate a global risk score by considering the different importance of risk factors and obtaining the related vector of weights through a MCDM approach capable to model interrelationships bounding the elements of analysis;
- to integrate the FMECA and BN frameworks to generally improve the process of risk assessment and achieve more accurate results to be translated into the implementation of more effective decisions;
- to carry out a deep SCR assessment in the field of the alimentary industry on the basis of expert judgements to provide logistic managers operating in this sector with useful insights for SCR management.

This approach can effectively support analysts in implementing risk management procedures on the basis of more reliable risk evaluations, the latter being led by overcoming the main drawbacks of traditional FMECA assessments and by exploiting benefits derived from BN-based approaches.

2.1 Embodying the Human Contribution into the RPN Calculation

FMECA is a systematic procedure to identify and analyse all the failure modes potentially involving systems or their main components, through the definition of the related causes and effects. The method aims to prioritise the failure modes under analysis by calculating the index called Risk Priority Number (RPN) for each of them. The RPN is traditionally derived from the multiplication of three main factors, namely severity (S), occurrence (O) and detection (D):

$$RPN = S \times O \times D. \tag{1}$$

Severity expresses the intensity of the impact that the occurrence of a given failure mode could have on the global system performance. Occurrence is an estimate of the frequency of occurrence of a failure mode within a given time lapse. Detection evaluates the probability of correct failure identification. The three risk factors are generally ranged within discrete intervals. Table 1 presents possible evaluation scales, adapted from the FMECA guidelines [25], which can be assumed for the parameters. As observed in Tables 1a and b, higher linguistic evaluations of severity and occurrence lead to higher RPN values. On the contrary, as shown in Table 1c,

Table 1 Evaluation scales for RPN parameters adapted from [25]

(a) Scale for severity

Evaluation	Meaning	Value
Very High (VH)	Loss of primary function, non-compliance with government regulation	5
High (H)	Significantly reduced level of performance, customer very dissatisfied	4
Moderate (M)	Moderately reduced level of performance, customer dissatisfied	3
Low (L)	Lowly reduced level of performance, customer somewhat dissatisfied	2
Very Minor (VM)	Defect noticed by discriminating customers, almost no discernible effect	1

(b) Scale for occurrence

Evaluation	Meaning	Probability	Value
Very High (VH)	Highly probable occurrences	$P_i \geqslant 1 \times 10^{-1}$	5
High (H)	Repeated occurrences	$1 \times 10^{-2} \leq P_i \leq 5 \times 10^{-2}$	4
Medium (M)	Occasional occurrences	$1 \times 10^{-3} \leq P_i \leq 5 \times 10^{-3}$	3
Low (L)	Relatively few occurrences	$1 \times 10^{-4} \leq P_i \leq 5 \times 10^{-4}$	2
Very Low (VL)	Probability of occurrence almost null	$P_i \leq 1 \times 10^{-5}$	1

(c) Scale for detection

Evaluation	Meaning	Value
Very High (VH)	Very high chance to detect a potential cause and subsequent failure mode	1
High (H)	High chance to detect a potential cause and subsequent failure mode	2
Moderate (M)	Moderate chance to detect a potential cause and subsequent failure mode	3
Low (L)	Moderate chance to detect a potential cause and subsequent failure mode	4
Very Minor (VM)	Remote chance to detect a potential cause and subsequent failure mode	5

higher linguistic evaluations of detection reflect lower risk conditions. This is why the corresponding numerical scale is inversely proportional to the linguistic assessments.

As already underlined, the existing literature points out various drawbacks for the traditional RPN calculation. Such a calculation could be further improved accordingly.

Novel aspects with respect to those traditionally used for the RPN calculation are proposed in this paper. First, note that risks emerged from the identification process are still going to be assessed on the basis of evaluations attributed by experts to severity and occurrence probability, two of the three parameters considered by the traditional FMECA approach. However, instead of considering the probability of detection as a third risk parameter, we are going to introduce a new factor for risk evaluation within the FMECA framework, namely the human factor. The detection parameter is excluded from the analysis because, as underlined in [41], this parameter is not relevant for SCR evaluation, that is our main field of application. Moreover, various other studies exclude this aspect from FMECA and risk classification also in other application fields. Some authors [36, 47, 48] perform effective calculations of risk criticality by multiplying just severity and occurrence, without including the contribution of detection, whose estimation, in some cases, may be considered as too complex with respect to the expected benefits.

Table 2 Evaluation scale proposed for the human factor

Evaluation	Meaning	Value
Very High (VH)	Very high probability of human error during the task execution	5
High (H)	High probability of human error during the task execution	4
Medium (M)	Moderate probability of human error during the task execution	3
Low (L)	Low probability of human error during the task execution	2
Very Low (VL)	Almost null probability of human error during the task execution	1

Furthermore, especially for those business processes for which the role played by humans is crucial (e.g. supply chain management), traditional procedures of risk assessment should be restructured and updated in order to take into account a comprehensive set of human factors. In such a direction, our methodological approach may be effectively supportive to address the concept of probability of human error, by integrating an estimation of the human contribution and assessing opportunities of improvement. The human factor is linked to the concept of human error probability and, by synthesising the degree of human experience, professional training, skills, and work-related stress when leading a given task, it considers the presence of human resources in charge of specific activities and their contribution to risk. Thus, we propose the evaluation scale shown in Table 2 to assess the human factor on the basis of proper surveys led within the context of reference. Specifically, with relation to the potential occurrence of each identified risk, a decision-making team is asked to express judgments aimed at quantifying the human factor within the range comprised between the unity and a maximum value of 5. The evaluation is influenced by such aspects as high emotive stress level, high level of responsibility, time shortage, lack of familiarity with the task, possible conflicts of interest, cultural difficulties, and so on [43]. The three considered risk parameters, namely severity (S), occurrence (O) and human factor (H), will be evaluated by means of the five-point scales respectively proposed in Tables 1a, b and 2. The higher/lower the evaluation of these parameters, the higher/lower the contribution to the risk function. The main sub-criteria impacting on each risk parameter will be formalised in the next subsection.

Once collected the numerical evaluations of the three parameters for each identified risk, we propose to compute the integer weighted geometric mean value (**int**) associated to each risk as a final score (global risk value). Specifically, final risk scores updating the traditional RPN will be calculated as follows:

$$R = \text{int}[S^{w_S} \times O^{w_O} \times H^{w_H}], \tag{2}$$

w_S, w_O and w_H being determined using ANP, as explained more in detail on the following. Observe that ‘int’ means the largest integer less than a given number, also called ’floor’ function.

2.2 The Analytic Network Process to Weight Risk Factors

The ANP is a well known MCDM technique, first developed by Saaty [51] on the basis of the Analytical Hierarchy Process (AHP) [50]. The latter has been extensively applied to solve a huge range of real applications by calculating criteria weights and, in general, ranking decision-making elements in a structured way. However, the AHP is useful in specific contexts where many preliminaries have to be assumed, and loses power when scenarios get more complicated. One of the most significant limitations of the AHP consists in assuming the condition of independence among the elements under analysis, what represents a strong constraint in practical contexts. In other terms, elements to be pairwise compared in AHP have to be assumed as independent from each other, what does not correspond to the practical reality in the vast majority of cases, and may lead to not feasible or ineffective results. In general, when analysing a set of decision-making elements, it is difficult to assume that they are completely independent from each other. In our particular case, aiming to calculate the weights of severity, occurrence and human factor, the assumption of independence among these risk parameters do not appear to be realistic.

More in detail, there are specific cases in which severity and occurrence may be considered as mutually independent, what implies that their evaluations are neither directly nor indirectly proportional. In these scenarios, a low (or high) occurrence probability linked to a specific risk has no impact on the related severity. Similarly, the fact that a risk has associated low (or high) severity can be assumed as independent from its related occurrence probability. However, in many other cases, for example for systems subjected to the wear phenomenon, this assumption cannot be made, since it is clear that severity and occurrence influence each other (more frequent risks are progressively more severe and vice versa). When it comes to the human factor, we claim it cannot be assumed as independent from severity and occurrence in any case, since a relationship of influence exists in both cases. Let us further clarify this concept. When a risk has associated high severity or high occurrence probability, the human factor can be indeed high accordingly, then directly proportional, because of the potential high level of stress that human resources may experience and accumulate in leading the related task, what may have a consequential impact on the potential occurrence of human errors. Moreover, there may be cases in which high levels of severity and occurrence for a given risk are further impacted by the lack of professional experience and suitable training from the personnel in charge, something that may lead to significantly higher levels of risk on the whole. However, even high degrees of experience may result in a lack of professional attitude and increase the risk level due to potential excessive self-confidence from the deputed personnel and related lack of multiple controls when leading tasks.

On the basis of these observations and given the links existing among the chosen risk factors, the use of the ANP is herein suggested to calculate their weights for the process of risk evaluation. Differently from the AHP, the ANP is indeed capable to capture the innate interdependent nature of the faced decision-making problem elements. The ANP application will be focused on analysing those sub-criteria relevant for the main factors' evaluations, formalised in Fig. 1, and their different contribution from the decision-maker perspective.

As we can observe, severity, occurrence and human factor are the three main clusters of the ANP problem. They are respectively made of three, one and three nodes. Specifically, such elements as time, quality and cost are the main sub-criteria influencing the severity evaluation, being particularly critical in determining successful productivity performance and general results of processes. Negative impacts in terms of time, quality and cost directly lead to higher risk evaluation. The probability of occurrence uniquely refers to the second parameter since highly frequent occurrences increase the global risk evaluation. One has to note that global risk scores can be mitigated when occurrences are less frequent, even in correspondence of high values of severity, and vice versa. With relation to the human factor, its main sub-criteria have been synthesised as: work condition (including such aspects as safety and security, hygiene of workplaces and work environment, cooperation and communication among workers, accessibility of information about processes, and so on); professional

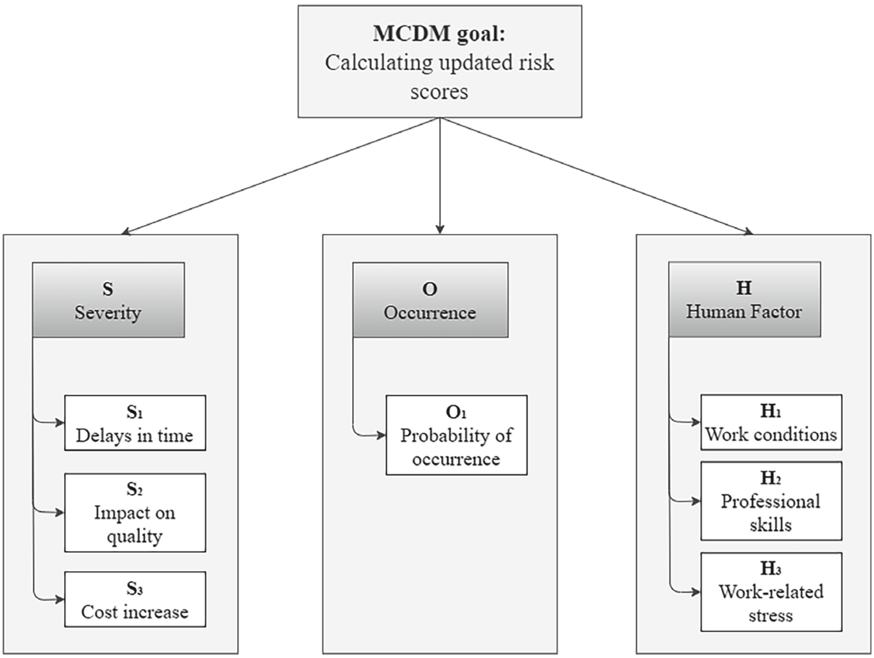

Fig. 1 Hierarchy structure representing the main elements for the ANP application

skills (taking into account the personal/professional background of workers along with their degree of training and qualifications achieved for leading specific tasks); and work-related stress (which derives from particular work conditions—for example cases in which responsibility about tasks is not shared among workers, excessive workload, absence of gratification or sense of belonging to the company—and can definitely negatively impact the global risk evaluation). A concise description of the ANP implementation can be consulted, for example, in [13], where the technique has been applied as a part of risk evaluation framework for a real complex manufacturing system.

2.3 Integrating FMECA and BN Frameworks

As widely explained, our objective consists in integrating the human factor in FMECA-based risk assessment by taking advantage of BNs' ability for inference, which incorporates uncertainty. This enables us to obtain valuable information for risk assessment to help decision-making processes in planning, operating, maintenance etc. in industry, and other fields. With relation again to the traditional RPN calculation, apart from the already discussed weaknesses, one has to observe as FMECA does not consider the potential simultaneous occurrence of multiple failure scenarios. This aspect can be effectively taken into account by integrating traditional FMECA and a BN-based approach, an integration considered as beneficial in the field of risk analysis [65] in terms of modelling complex systems, making accurate predictions about parameters' values, and computing with precision the occurrence probability of failure events [65]. However, this aspect is not evaluated by this research. We specify that we are herein modelling the interconnected structure of variables involved within the risk assessment process to eventually understand which failures have associated a significant number of interconnections. The failure resonance issue may be object of future research.

A BN is a compact and modular distribution of random variables represented through an acyclic graph in which variables are placed at the nodes, and the arcs are loaded with probabilities [1, 29, 42]. A BN is a twofold object: it has a qualitative aspect, i.e. the graph showing the mainly cause-effect relationships, and the quantitative distribution of probabilities, as affirmed by Weber et al. [60]. This last research has been cited in a work recently published by Steijn et al. [55] who underline as methodological approaches based on BN modelling can be of interest in many fields connected with the risk management process. With this regard, the authors mention specific application areas of BN where the role of safety for human resources as well as related risk assessment are particularly crucial, such as offshore platform maintenance, maritime industry, air transportation, and so on. Proposals making use of BN in this field have been also supported by fuzzy rule-based systems considering exper feedback for failure identification, as showed in [23]. We would like to further stress that, with respect to the current state of the art, the main novelty of our paper consists in proposing the integration between FMECA and BN supported by a MCDM perspective and by introducing for the first time the human factor within the set of parameters for risk evaluation.

In a BN, evidence information propagates and updates our belief (a priori probability) on non-observed variables to get new a posteriori) knowledge. This is an objective of inference, including diagnosis, prediction, inter-causal relationships, etc. Conditional probabilities (and the structure itself) can be learnt from data. In this sense, BNs constitute optimal decision-making tools, which also enable simulation to observe outcomes derived from a range of actions. The capability of a BN to model several (many) variables and their interconnected structure in a complex network system refers to:

1. identifying relations of conditional independence (Ind) of a (generic) node A_i with respect to its non-descendants (NoDesc) given the values of its parents (Pa);

$$\mathrm{Ind}(A_i; \mathrm{NoDesc}(A_i)|\mathrm{Pa}(A_i)); \tag{3}$$

2. given the conditional probability tables, determining the joint probability distribution

$$P(A_1, \ldots, A_n) = \prod_{i=1}^{n} P(A_i|\mathrm{Pa}(A_i)); \tag{4}$$

3. performing inference: calculating a posteriori probabilities, $\mathbf{P}$, for variables of interest, $\mathbf{X}$, given observed values of some variables or evidence, $\mathbf{e}$, still considering hidden variables, $\mathbf{Y}$,

$$\mathbf{P}(\mathbf{X}|\mathbf{e}) = \alpha\mathbf{P}(\mathbf{X}, \mathbf{e}) = \alpha\sum_{\mathbf{y}}\mathbf{P}(\mathbf{X}, \mathbf{e}, \mathbf{y}), \tag{5}$$

where α is a normalizing factor, and $\mathbf{P}(\mathbf{X}|\mathbf{e})$ expresses the (vector) probability of variables in vector $\mathbf{X}$, given the (vector) evidence $\mathbf{e}$. Observe that $\alpha = \frac{1}{P(\mathbf{e})}$, a value whose calculation can be avoided; in effect, the components of $\mathbf{P}(\mathbf{X}|\mathbf{e})$ have to add up to 1, and this can be achieved by calculating $\sum_{\mathbf{y}}\mathbf{P}(\mathbf{X}, \mathbf{e}, \mathbf{y})$ and normalizing to sum 1.

3 Real-World Application on the Alimentary Industrial Sector

3.1 Problem Setting

In the previous conference paper [12], a SCR problem involving the warehouse design and management for a real Italian manufacturing company, operating in the sector of alimentary industry, was considered. We are now aimed at facing the same

Table 3 SCRs description

ID	SCR	Meaning
SCR_1	Safety	Human safety and workplaces hygiene
SCR_2	Damages	Finite products/packaging damaged
SCR_3	Communication	Communication/flexibility problems with suppliers
SCR_4	Transportation	Transportation difficulties/network complexity
SCR_5	Commerce	Commercial problems/unpredictable price rise
SCR_6	Performance	Low logistic performance
SCR_7	Disruptions	Loading/Unloading process disruptions
SCR_8	Delivery	Inefficient delivery of finite products/packaging
SCR_9	Environment	Inadequate environment conditions
SCR_{10}	Strategy	Inefficient strategy/organisational problems

decision-making problem, this time extending the study from the single company to the whole sector perspective. First, we widen the practical analysis and involve various companies—all of them belonging to the same industrial sector of interest—to join the survey. The present case study aims to support decision-makers operating in the logistic sector of the alimentary industry in the difficult task of optimising new procedures of warehouse operations as well as best practices to maximise their incomes by simultaneously coping with the safety updates established by the COVID-19 protocol [24]. Ten major SCRs (Table 3) potentially impacting the warehouse reorganisation problem have been identified and various brainstorming sessions have been led to carry on the risk assessment.

To this end, a sample of four manufacturing companies has been considered to carry out the evaluation. Table 4 provides information about the specific core business of companies within the alimentary sector and the composition of the related decision-making teams (visually synthesised in Fig. 2) involved to assess severity, occurrence and human factor via the scales given in Tables 1a, b and 2.

As it can be seen from data provided in Table 4, the entire decision-making panel is made of sixty stakeholders with heterogeneous professional backgrounds and diverse degree of responsibilities within the companies. This will be helpful to gain a comprehensive overview of SCR management by taking into account opinions of experts involved at various levels of the hierarchical structures of the companies object of study. Decision-makers have been further grouped into the following five main categories based on similarities in their roles: manager, director, warehouse worker, production worker, and other worker. Such a classification has been devised to study how decision makers' roles influence final evaluations. Specifically, the role "manager" includes three general managers, four technical consultants and two quality control supervisors. The role "director" includes four directors of the Safety and Security System, one warehouse director, one production director, three workers representatives for safety and security, two loading/unloading area supervisors, and one maintenance crew leader. Lastly, thirty-nine workers have been interviewed

Table 4 Companies' details and decision-making (DM) teams

ID company	Core business	DM team
IND_1	Marine salt manufacturing	General Manager (1), Technical Consultant (1), Quality Control Supervisor (1), Director of the Safety and Security System (1), Warehouse Director (1), Production Director (1), Workers Representative for Safety and Security (1), Loading/Unloading Area Supervisor (1), Maintenance Crew Leader (1), Warehouse Worker (4), Production Worker (3), Other Worker (4)
IND_2	Virgin olive oil production	General Manager (1), Technical Consultant (1), Director of the Safety and Security System (1), Workers Representative for Safety and Security (1), Warehouse Worker (5), Production Worker (5)
IND_3	Wine production	General Manager (1), Technical Consultant (1), Quality Control Supervisor (1), Director of the Safety and Security System (1), Workers Representative for Safety and Security (1), Loading/Unloading Area Supervisor (1), Warehouse Worker (4), Production Worker (3)
IND_4	Wine production and bottling	Technical Consultant (1), Director of the Safety and Security System (1), Warehouse Worker (6), Production Worker (4), Other Worker (1)

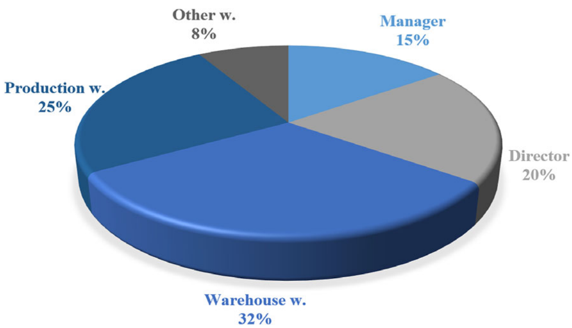

Fig. 2 Composition of the interviewed decision-making panel

and then categorised according to their specific job requirements to reflect possible different perspectives about SCR evaluation (adhering to specific practical tasks): nineteen of them have been assigned to the "warehouse worker" category, fifteen to the "production worker" category and the remaining five to the "other worker" category, since they mainly develop their tasks in external areas.

3.2 Evaluations Collection and ANP Application for Scoring Risks

Once established the boundaries as well as the main elements of analysis and composed the decision-making panel, each individual was independently asked to provide numerical evaluations reflecting their own personal perceptions about the three risk factors for each SCR of Table 3. To exemplify the procedure of input data collection, Table 5 shows the evaluations provided by one decision maker from each category belonging to the first company (IND_1). Specifically, Table 5a reports the evaluations that have been attributed to the three risk factors by a decision maker belonging to the "manager" category of the considered company, along with the calculated global risk score for each SCR; Table 5b reports the evaluations attributed by an expert of the "director" group; Table 5c–e, respectively report the evaluations attributed by one worker whose tasks are accomplished in the warehouse, one worker involved in

Table 5 Examples of evaluations from experts belonging to company IND_1

(a) Evaluations from the "manager" group

ID	S	O	H	Score
SCR_1	5	2	3	3
SCR_2	2	2	3	2
SCR_3	3	2	1	2
SCR_4	3	2	2	2
SCR_5	4	3	2	3
SCR_6	4	2	3	3
SCR_7	4	3	3	3
SCR_8	3	2	3	3
SCR_9	4	5	2	3
SCR_{10}	3	1	3	2

(b) Evaluations from the "director" group

ID	S	O	H	Score
SCR_1	5	3	2	3
SCR_2	2	2	2	2
SCR_3	4	3	1	2
SCR_4	3	2	2	2
SCR_5	2	3	2	2
SCR_6	4	2	1	2
SCR_7	5	2	1	2
SCR_8	3	2	2	2
SCR_9	4	4	3	4
SCR_{10}	3	3	2	3

(c) Evaluations from the "warehouse worker" group

ID	S	O	H	Score
SCR_1	4	3	3	3
SCR_2	3	3	1	2
SCR_3	4	3	2	3
SCR_4	4	2	2	3
SCR_5	3	2	2	2
SCR_6	4	3	3	3
SCR_7	4	3	3	3
SCR_8	3	2	2	2
SCR_9	4	3	3	3
SCR_{10}	3	2	3	3

(d) Evaluations from the "production worker" group

ID	S	O	H	Score
SCR_1	5	4	2	3
SCR_2	3	2	2	2
SCR_3	3	3	2	3
SCR_4	3	2	2	2
SCR_5	3	2	2	2
SCR_6	3	2	3	3
SCR_7	4	3	2	3
SCR_8	3	3	2	3
SCR_9	4	5	3	4
SCR_{10}	3	2	2	2

(e) Evaluations from the "other worker" group

ID	S	O	H	Score
SCR_1	4	2	2	3
SCR_2	2	3	1	2
SCR_3	3	2	2	2
SCR_4	3	2	2	2
SCR_5	3	2	2	2
SCR_6	3	3	2	3
SCR_7	4	3	2	3
SCR_8	3	3	2	3
SCR_9	3	3	2	3
SCR_{10}	3	3	1	2

Fig. 3 SCRs evaluations from the IND_1 DM team

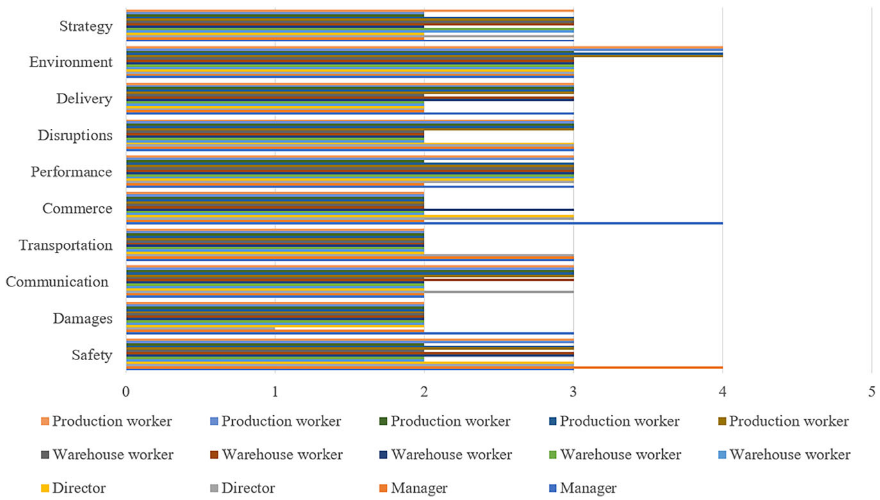

Fig. 4 SCRs evaluations from the IND_2 DM team

the production process and one worker with other expertise. The global risk scores associated to SCRs have been calculated for each decision-maker by computing the integer weighted geometric mean values of the attributed evaluations through Formula (2). Factors' weights, calculated by means of the ANP, are the following: $w_S = 0.3447$, $w_O = 0.2494$ and $w_H = 0.4059$.

Figures 3, 4, 5, 6 graphically show the risk scores distribution for the interviewed sample of companies.

We detail now the process of weights calculation by using the ANP. After collecting numerical evaluations for the factors, factors weights to apply Formula (2)

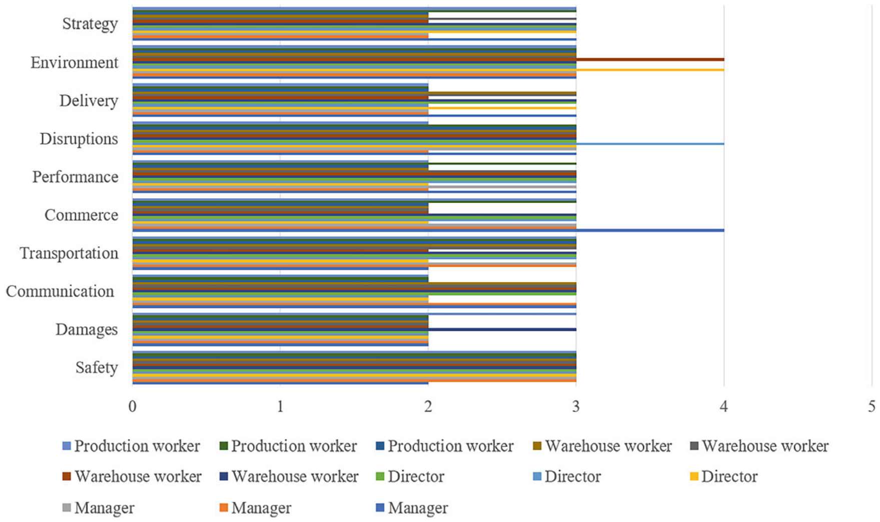

Fig. 5 SCRs evaluations from the IND_3 DM team

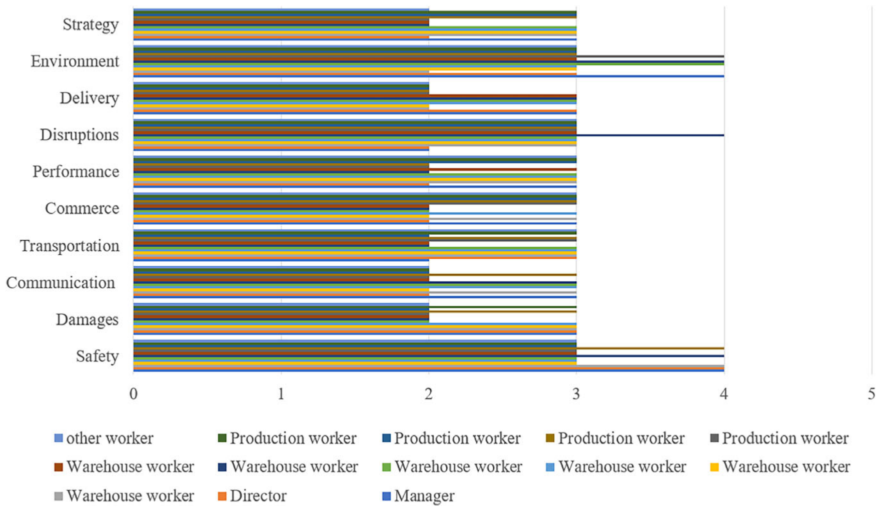

Fig. 6 SCRs evaluations from the IND_4 DM team

have been attributed by collecting judgments of pairwise comparisons for all the decision-making elements provided in Fig. 1, that is, risk factors and main related sub-criteria, along with specifications about interdependence relationships (graphically represented in Fig. 7).

Once established relationships of influence amongst elements and organised all the provided pairwise comparisons' judgments, the AHP has been applied to calculate

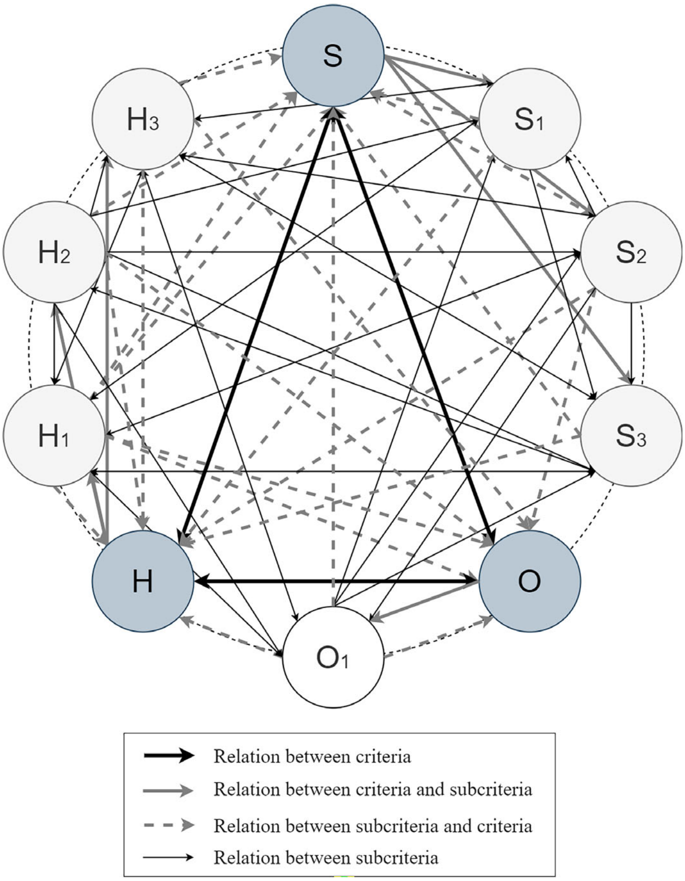

Fig. 7 Interdependence relationships among risk factors and subcriteria

the priorities reported in the unweighted matrix (Table 6) of the ANP procedure. By normalising the columns of the unweighted matrix to sum one, the weighted matrix (Table 7) is obtained.

The limit matrix is then calculated by raising the weighted matrix to successive powers. Each of these powers captures all transitivities of the order of that power. According to Cesaro Summability, the limit of these powers, is equal to the limit of the sum of all the powers of the matrix. This way all the so-called steady state priorities are captured. The limiting matrix, whose convergence is assured by its stochasticity, have equal columns. Any of these columns corresponds to the Perron eigenvector of the weighted matrix, and the normalised elements of the columns express the final weights calculated by means of the ANP, see [52]. Normalised values from the limit matrix related to risk factors and sub-criteria are given in Table 8 along with

Table 6 Unweighted matrix

UM	Goal	S	O	H	S_1	S_2	S_3	O_1	H_1	H_2	H_3
Goal	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
S	0.443	0.000	0.500	0.750	0.333	0.250	0.333	0.200	0.250	0.250	0.250
O	0.169	0.333	0.000	0.250	0.000	0.500	0.000	0.600	0.250	0.250	0.250
H	0.388	0.667	0.500	0.000	0.667	0.250	0.667	0.200	0.500	0.500	0.500
$\mathbf{S_1}$	0.167	0.260	0.000	0.000	0.000	0.195	0.000	0.167	0.141	0.164	0.121
$\mathbf{S_2}$	0.167	0.327	0.000	0.000	0.000	0.000	0.000	0.167	0.141	0.164	0.121
$\mathbf{S_3}$	0.167	0.413	0.000	0.000	0.142	0.088	0.000	0.167	0.141	0.164	0.121
$\mathbf{O_1}$	0.074	0.000	1.000	0.000	0.000	0.225	0.000	0.000	0.248	0.136	0.213
$\mathbf{H_1}$	0.165	0.000	0.000	0.260	0.429	0.246	0.327	0.167	0.000	0.186	0.424
$\mathbf{H_2}$	0.132	0.000	0.000	0.413	0.000	0.000	0.413	0.000	0.000	0.000	0.000
$\mathbf{H_3}$	0.128	0.000	0.000	0.327	0.429	0.246	0.260	0.332	0.329	0.186	0.000

Table 7 Weighted matrix

WM	Goal	S	O	H	S_1	S_2	S_3	O_1	H_1	H_2	H_3
Goal	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
S	0.222	0.000	0.250	0.375	0.167	0.125	0.167	0.100	0.125	0.125	0.125
O	0.085	0.167	0.000	0.125	0.000	0.250	0.000	0.300	0.125	0.125	0.125
H	0.194	0.334	0.250	0.000	0.334	0.125	0.334	0.100	0.250	0.250	0.250
$\mathbf{S_1}$	0.084	0.130	0.000	0.000	0.000	0.098	0.000	0.084	0.071	0.082	0.061
$\mathbf{S_2}$	0.084	0.164	0.000	0.000	0.000	0.000	0.000	0.084	0.071	0.082	0.061
$\mathbf{S_3}$	0.084	0.207	0.000	0.000	0.071	0.044	0.000	0.084	0.071	0.082	0.061
$\mathbf{O_1}$	0.037	0.000	0.500	0.000	0.000	0.113	0.000	0.000	0.124	0.068	0.107
$\mathbf{H_1}$	0.083	0.000	0.000	0.130	0.215	0.123	0.164	0.084	0.000	0.093	0.212
$\mathbf{H_2}$	0.066	0.000	0.000	0.207	0.000	0.000	0.207	0.000	0.000	0.000	0.000
$\mathbf{H_3}$	0.064	0.000	0.000	0.164	0.215	0.123	0.130	0.166	0.165	0.093	0.000

the related percentage weights. We specify that weights of sub-criteria have been normalised according to the related risk factor.

As can be appreciated, higher importance has been attributed to the human factor. It means that evaluations of this parameter are going to primarily impact the final risk assessment for the industrial sector under study. Furthermore, the human factor itself appears to be more influenced by such aspects as work-related stress and safe work conditions, rather than workers' professional skills. After the human factor, the severity parameter presents a prominent weight with respect to the occurrence factor. In its turn, severity appears to be primarily influenced by economic aspects, but also significantly impacted by potential problems involving quality and times.

Table 8 Risk factors and sub-criteria's weights

Risk factor	Value	Weight (%)	Sub-criterion	Value	Weight (%)
S	0.172	34.47	S_1	0.052	30.44
			S_2	0.052	30.84
			S_3	0.066	38.72
O	0.125	24.94	O_1	0.093	100.00
H	0.203	40.59	H_1	0.088	36.90
			H_2	0.055	23.38
			H_3	0.094	39.72

3.3 BN-Based Modelling and Discussion of Results

We are now going to exploit the ability of BNs to model variables and their interconnected structure. Relations of conditional independence will be better identified and their conditional probability table will be determined as well as their joint probability distribution in order to eventually develop a BN integrating the human factor in FMECA-based risk assessment. Figure 8 and Table 9, respectively, show the final network of relations and the related strengths, measured by mutual information. Results have been obtained by iterating the PC algorithm (named after its authors, Peter and Clark, from [54]) through the Handling Uncertainty in General Inference Network (HUGIN) software for BN learning, commonly used to model relations of conditional dependence within the set of observed data [1]. HUGIN develops a causal probabilistic network that can be progressively updated by means of a posteriori probability distribution [4]. As previously observed, one can note that both SCRs and decision-makers' roles are considered as variables in the network. Figure 9 lastly shows the incorporation of evidence into the BN. In the upper part we present marginal probabilities of all model variables while in the lower part the conditional probabilities given the evidence Role = Director are shown.

We can derive various considerations by observing the results reported in the final network of relationships. First of all, variables appear to be related in a way to form an interconnected graph where no element remains isolated. We also point out the presence of strong mutual relations within the analysed set of variables including SCRs and decision-makers' roles, highlighted by the thickness of the arrows.

Immediate practical interpretations of results are described as follows. Safety and transportation risks, apart from being mutually linked, appear to be the variables with a higher number of associated interconnections. Specifically, safety is further directly related to such aspects as disruptions, environment, and performance. According to the provided judgments, indeed, evaluations attributed to the mentioned risks influence each other. In its turn, transportation is further mainly related to commerce, damage, delivery and environment. To note, while the connection between environment and safety is significant, environment and transportation are linked by means of a thinner arrow, which highlights a condition of weaker connection with respect

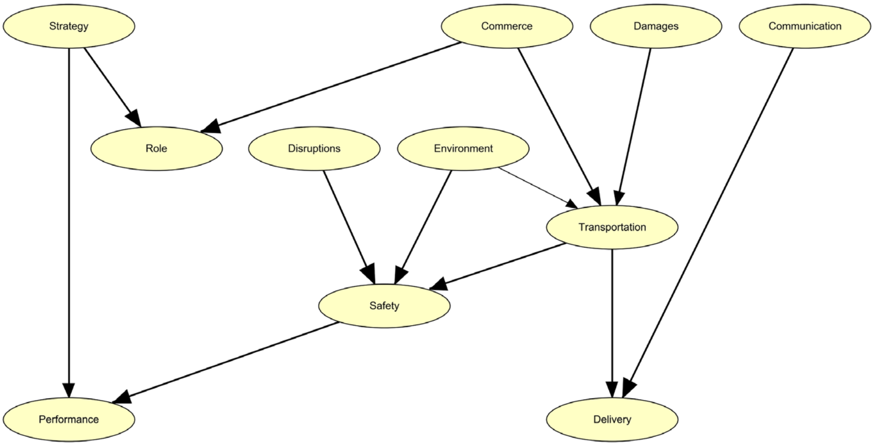

Fig. 8 Network of relationships

Table 9 Strength of relationships measured by mutual information (the higher the value the stronger the relationship)

Edge	Mutual information
Communication → Delivery	0.11
Disruptions → Safety	0.11
Commerce → Role	0.11
Safety → Performance	0.10
Strategy → Role	0.09
Commerce → Transportation	0.09
Environment → Safety	0.09
Transportation → Safety	0.09
Transportation → Delivery	0.07
Strategy → Performance	0.06
Damages → Transportation	0.05
Environment → Transportation	0.01

to the other relations. This result is justified by the fact that, despite environment is important for transportation issues, these last ones are more sensitive to commercial problems, potential product/packaging damages and inefficient deliveries. Moreover, one has to note the remaining important connections detected between strategy and performance and between delivery and communication throughout the supply chain.

Another important result refers to the dependence between the variables representing role and commercial/strategy risks. Differently from other types of risks, for which evaluation is more objective and independent on the role of the decision-maker who is expressing opinions, commercial and strategy risks are role-sensitive; in other

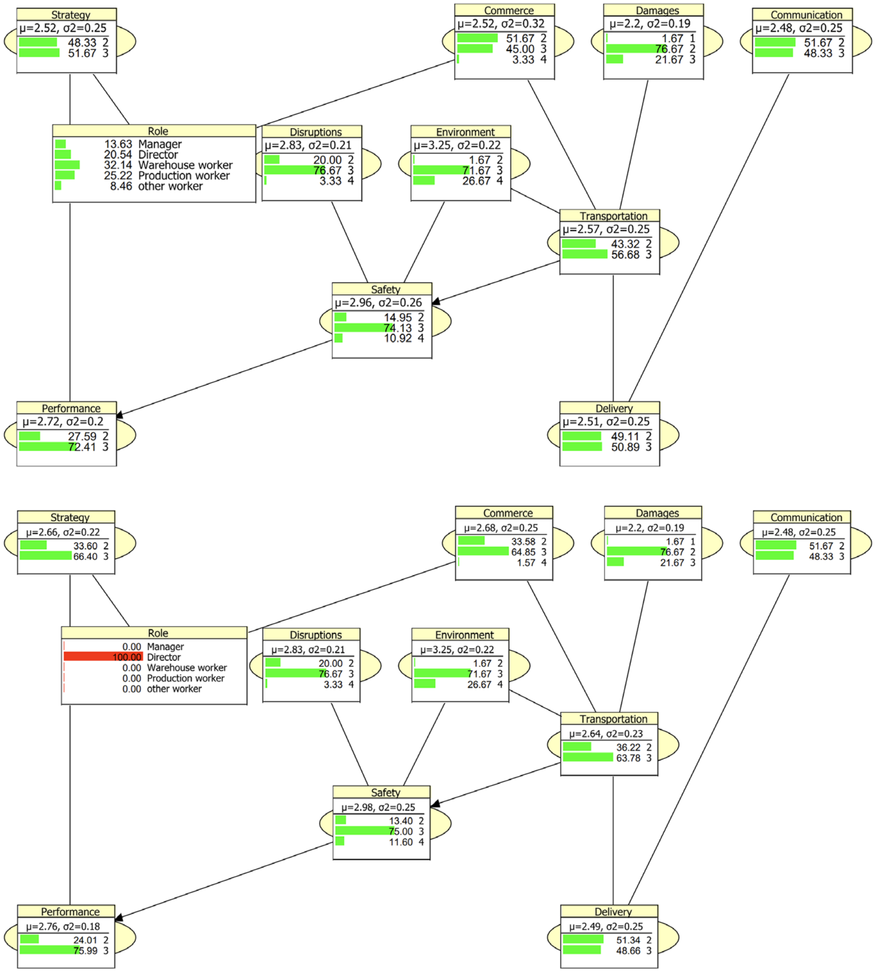

Fig. 9 Entering evidence Role = Director into the BN

terms, differently perceived by managers, directors and workers. This consideration leads to the fact that decision-makers belonging to different categories will attribute significantly different evaluations to the parameters related to commercial problems and/or unpredictable price raises as well as to inefficient strategy and/or organisational problems. Managers typically associate them with higher values, directors with medium values, and workers with lower values.

When it comes to managerial insights, by analysing the final results it is immediate to understand as risk management actions should be primarily aimed at reducing/preventing supply chain risks connected with human safety and workplaces hygiene as well as transportation difficulties deriving from network complexity. Improvements in managing these two SCRs may have significant positive impact on the other related risks and, in general, on the whole supply chain performance. It is also important to note as dealing with the mentioned aspects is fundamental to cope with current business scenarios dangerously affected by COVID-19 pandemic and be in line with requirements of existing regulations in the supply chain risk management field. Apart from safety and transportation, it is also particularly important to deal with such aspects as commercial problems, disruptions of loading/unloading processes and environment conditions. Indeed, as we can appreciate from Fig. 9, these SCRs have in some cases associated a higher global risk score. Implement proper actions aimed at reducing these scores would be then desirable to generally improve final outputs and supply chain processes for the alimentary industrial sector.

4 Conclusions

The presented research originates from the utmost importance of leading accurate analyses of risk assessment in business contexts. This undoubtedly represents a fundamental step to proceed towards an effective risk management and improve business performance.

The traditional FMECA analysis has been presented and recalled as a common way for risk evaluation purposes on the basis of the calculation of the RPN index for each failure mode identified for complex systems. Traditional FMECA is herein developed by first reviewing and updating its risk parameters with the aim of embodying the human factor into the risk function calculation. A decision-making approach making use of the ANP technique has been proposed to weight the selected parameters so that the final risk score can been calculated by taking into account their different importance. Once clarified the risk function calculation process, a BN-based perspective has been integrated for analysing causal relationships for risk evaluation and deriving probabilistic inference among the most significant elements of analysis.

The proposed approach has been applied to a real case study on the SCRM field. Specifically, a deep SCR assessment in the field of the alimentary industry has been led on the basis of judgements provided by a decision-making team made of sixty experts. A sample of four companies operating in the alimentary sector has been taken into account and final results, which show the presence of significant dependence among the considered variables, can be helpful to provide logistic managers operating in this sector with useful insights for SCR management.

Bayesian networks represent a modeling tool that can capture well relations between variables of the model especially if they can be expressed in the form of conditional independence. This is especially useful when a variable is influenced by another variable only indirectly through other variables. The BN models can be further enhanced by considering only a restricted local structure of conditional probability tables, for example, by imposing monotonic relations among the variables. This can help to learn better models especially when learning data sets are small. For future analyses, we may also consider the integration of economic criterion among the set of significant risk parameters as well as such other aspects as the failure resonance.

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