Supply chain chronic losses and risk interdependencies: A Bayesian Belief Network approach

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Abstract

Supply Chain Risk Management (SCRM) has become integral to firm governance and risk interdependencies, despite limited attention, significantly impact risk analysis and mitigation. Recurrent risks, resulting from consistent disturbances, generate chronic losses and are critically affected by other related risks. This work enhances the assessment of chronic losses with interdependent risks, building upon an existing Bayesian Belief Network (BBN) approach for risk interdependencies in SCRM, combining expected utility theory to address the complex, interconnected nature of risks. This work advocates a change in existing approaches to properly evaluate chronic losses often underestimated due to decision makers' expectations. The research shows that the impact of recurrent risks may be underestimated by other approaches based on their frequency, undermining confidence in mitigation strategies. This work not only presents a novel approach to risk assessment, but also highlights the importance of studying causal interdependencies, and emphasizes the need to consider low-probability and high-impact risks but also recurrent, seemingly minor risks in SCRM processes.

Keywords: Supply Chain Risk Management, Risk Interdependencies, Bayesian Belief Networks, Chronic Losses, Expected Utility

1 Introduction

Disruptions like the COVID-19 pandemic, the terrorist attacks against the World Trade Center, and the natural disaster in Japan in 2011 have increased the interest of researchers and practitioners in the topic of Risk Management (RM) (Duong et al., 2022). Whilst risk is an ancient concept that has been studied since the beginning of the 20th century, RM has only recently emerged as a topic of interest, and it is conceived as a structured process aimed at coping with risks affecting organisations (Baloch et al., 2023). In particular, such a process aims not only to prepare firms for facing large and unpredictable disruptions but also to target recurrent operative risks that commonly affect an organisation (Ravulakollu et al., 2018).

Contemporary to the increasing relevance of RM, Supply Chain Management (SCM) has established itself as a critical task for ensuring the firm's capability to be competitive in the market (Shenoi et al., 2018; Thatte et al., 2013). The union of these topics gave rise to the concept of Supply Chain Risk Management (SCRM), which aims to deal with risks afflicting the supply chain, also called Supply Chain Risks (SCRs) (de Oliveira et al., 2017).

As highlighted by various authors, the literature on RM and SCRM has largely disregarded the study of risk interdependencies, which has hidden massive importance for effective risk analysis and mitigation (Ho et al., 2015; Fan & Stevenson, 2018). The relevance of such a topic is even higher in the context of SCRM because of the growing interdependency among the different entities of the chain.

In particular, recurrent risks, which result from disturbances with a consistent impact over time, generate chronic losses and are critically affected and amplified by other related risks and this issue is even more perceivable in practice (Tukamuhabwa et al., 2017). Indeed, by talking with a senior SCRM professional who has been working for several software and consultancy companies providing SCM solutions to large companies in many industries (for example, automotive and aerospace), it was perceivable the importance of chronic losses, which are, however, often "invisible" to the top management. In his opinion, companies tend to accept chronic losses as "the cost of the business". This underlines how much these losses are underestimated, often not even quantified, and kept unchanged because accepted as they are. The issue starts with the (lack of) identification of chronic losses and then their assessment. Furthermore, he (the senior SCRM professional) asserted the importance of studying new methodologies that can help in the identification of chronic losses. Their proper assessment will raise the awareness of the decision makers and improve associated mitigation strategies.

The research approach we are going to propose aims to consider this practical issue and the work here presented introduces an approach to properly considering risk interdependences, by reducing the potential biases introduced by decision makers. The perception of risk is subjective and is affected by several factors (Sasaki & Sakata, 2021); the interdependence of risks makes their assessment even more difficult (Fang et al., 2013; Mogre et al., 2016). Recurrent risks are critically affected and boosted by other related risks (Tukamuhabwa et al., 2017). The impact of recurrent risks is often underestimated, and one major reason truly refers to their frequency (Rivers & Arvai, 2007). Decision makers, and in general people, get used to common risks, and this reduces their perception of danger, thus creating a vicious circle: less attention, and increasing frequency (Rivers & Arvai, 2007). Recurrent risks are often the most detrimental that, if accumulated over the years, result in huge losses for companies (Tukamuhabwa et al., 2017).

These risks should also be considered from a multi-actor perspective. Different supply chain actors may have varying perceptions of risks due to differing operating contexts and processes (Mwesiumo et al., 2021; Ravulakollu et al., 2018). This variation necessitates an analysis of domino dynamics within the supply chain (Ravulakollu et al., 2018). Drawing on theories of cognitive psychology and neuroscience, Slovic et al. (2004) highlighted that humans comprehend risks through both analytic and experiential systems. The analytical system considers logical, data-driven decisions, while the experiential system involves intuitive, quick decisions not easily accessible to conscious awareness. People's perception of risk is influenced by their emotions towards potential outcomes, especially their dread or fear of unknown outcomes (Slovic et al., 2004). Effective risk management strategies must therefore account for these subjective perceptions and interdependencies to mitigate the cumulative impacts of risks across the supply chain.

A proper technique for modelling and analysing risk interdependencies and recurrent risks is needed (Mogre et al., 2016; Qazi et al., 2018). Among the various available methods, Bayesian Belief Network (BBN) has been indicated as one of the most promising tools for the study of risk interrelationships (Sharma & Sharma, 2015). BBNs are based on the famous Bayes' theorem and on the concept of conditional probability, which seems appropriate for modelling the concept of interdependency between risks (e.g., Qazi et al., 2017). In addition, this tool presents several features that make it suitable for the analysis of risk by considering such interdependencies.

Among the multiple applications of the BBN to different areas of interest in SCRM, the general approach developed by Qazi et al. (2018) seems to be one of the most promising. The key role of expected utility theory within this approach emphasizes the importance of the expectations of the decision makers within the risk assessment. Theoretical insights from works related to such a theory suggest that expectations reflecting a homeostatic attitude towards SCRM can lead to the underestimation of the impact of chronic losses (Rivers & Arvai, 2007).

This work proposes a BBN as a proper technique for the study of such interdependencies and moves from current applications of BBNs, by proposing a novel approach, to show how the impact of recurrent risks, which determine chronic losses, may be underestimated due to the decision maker's homeostatic attitude. The following analysis will be particularly relevant for practitioners because it will make available a reliable approach for measuring risk impact and highlighting the hidden effects of chronic losses that affect firm performance.

High-Frequency High-Impact (HF-HI) and Low-Frequency High-Impact (LF-HI) are primary targets in companies' strategies since considered by far the most disruptive (Chopra & Sodhi, 2004; Oke & Gopalakrishnan, 2009). Anyway, High-Frequency (seemingly) Low-Impact (HF-LI) risks, if kept monitored over time with the other concurrent risks, may reveal huge losses for firms' profitability that, in light of this, would redefine their priorities (Fang et al., 2013; Sheffi & Rice, 2005). In this sense, the present work draws attention to HF-LI risks that, together with the already well-known HF-HI and LF-HI risks, are accountable for heavy losses. Managers are consequently encouraged to look at risks with high frequency since HF may lower risk perception, and then, the proper evaluation of their real impact and interdependency with the others.

The paper is organized as follows. In *Section 2*, a review of the current state of the art on SCRM and risk interdependence is presented by focusing at the end on the implementation of BBNs for SCRM. In *Section 3*, the setting of the research and its objective, including the theoretical background supporting the main aim of the paper, are stated. In *Section 4*, the research methodology for chronic loss assessment is described. In *Section 5*, the results of the analyses are presented and in *Section 6* they are discussed. In *Section 7*, theoretical and managerial contributions, limitations and potential for future research are provided.

2 Literature review

The literature review below presents the main concepts of this work and provides an overview of the state of the art of SCRM, by introducing the key role played by risk interdependencies and BBNs.

2.1 Supply chain risk management and risk interdependencies

The relevance of SCM to the creation of competitive advantage for organisations is no longer disputed. However, if on the one hand, SCM can be a source of strategic benefits for companies, on the other hand, supply chain problems may significantly affect firm performance, disrupting or delaying material, information, and cash flows (Chopra & Sodhi, 2004). In addition, various trends in managing the supply chain, including outsourcing, supply base rationalisation, and just-in-time have increased supply chain exposure to risk (Fan & Stevenson, 2018).

Given the high significance of supply chain problems and the increasing exposure to the risk of supply chains, the concept of SCRM has been introduced as a separate topic of interest, emerging from the intersection of RM and SCM (de Oliveira et al., 2017). Whereas RM deals with any type of risk, SCRM is concerned with the risks affecting the flow and activities within the chain of the firms, also called SCRs. In particular, Tang (2006) defined SCRM as *"the management of supply chain risks through coordination or collaboration among the supply chain partners so as to ensure profitability and continuity"*.

There is a lack of consensus within the literature about the structure of the SCRM process: the number of steps involved, their names, and their objectives (Çıkmak & Ungan, 2022; de Oliveira et al., 2017; Khan et al., 2020). However, two prominent reviews (Ho et al., 2015; Fan & Stevenson, 2018) advocated that the SCRM process can be divided into four steps:

1. **SCR identification** *"involves gaining insights into any threat, uncertainty, vulnerability, and unexpected event that can become a source or trigger for risk to materialise*" (Tran et al., 2018). This stage is critical for managing SCRs because it enables the identification of all significant activities within the organisation and all the risks from these activities (Neiger et al., 2009). This step requires early judgment by the company, consisting of defining whether an SCR is significant and thus requiring further assessment and mitigation (Fan & Stevenson, 2018).
2. **SCR assessment** consists of analysing specific risk indicators through either qualitative or quantitative approaches to obtain individual and aggregated risk scores supporting the SCR mitigation and other management decisions (Tran et al., 2018). Researchers have focused on the assessment of two main indicators: the *probability of risk occurrence* and the *impact of risk consequences*. However, despite the importance of such parameters, additional risk indicators should be evaluated, including the interdependencies between risks (Choudhary et al., 2023). Indeed, SCRs are dependent events, as they depend on each other in terms of both likelihood of occurrence and severity of impact (Tran et al., 2018). Previously, researchers largely disregarded these aspects, by individually considering risks thus underestimating the potential impact on SCRM of their interrelationships (Fan & Stevenson, 2018). Recently, an extensive review of methodologies and applications in risk assessment within supply chains highlighted key parameters for assessing risks, considering their interdependence (Choudhary et al., 2023). These parameters include avoidance, cost, impact intensity, impact time, detectability, likelihood, risk exposure and expected utility. Among these, three parameters are particularly crucial for understanding interdependence and recurrent risks: impact intensity, which evaluates the severity of the risk event's effect on supply chain operations; impact time, which considers the duration over which the risk event's impact persists within the supply chain; and expected utility, which captures the value obtained conditional on the risk's influence (i.e., while the risk level goes high, taking these risks may be associated with a potential higher return).
3. **SCR mitigation** involves the development of appropriate countermeasures to control SCRs (Tran et al., 2018). The goal of this stage is to select and implement the best set of mitigation measures, that is, a mitigation strategy or policy to manage a previously identified and assessed SCR. Indeed, mitigating SCRs rarely involves a single action; rather, it consists of developing a plan with multiple mitigation steps. In these conditions, collaboration is essential in SCR mitigation as well as in the previous phases, as strategies of a buying firm often affect its suppliers with coordinated joint efforts, co-development of strategic relational capabilities and sharing of resources before, during, and after major incidents (Friday et al., 2018; Mwesiumo et al., 2021; Shahid et al., 2023). This perspective emphasizes that collaboration, integration and cooperation are elements critical to achieving supply risk mitigation.

4. **SCR monitoring** is the process of constantly updating SCR information and the selected treatment plan. Risk is never a static phenomenon; it needs to be constantly monitored to evaluate how it has changed and whether corrections to the mitigation strategy are necessary (Fan & Stevenson, 2018).

The four steps of the SCRM process advocate the relevance of the topic of risk interdependencies, however, in most of the existing SCRM processes and frameworks, risks are assumed to be independent during the SCR assessment phase (Zhang, 2016).

Consequently, the mitigation treatment plans only reflect the characteristics of individual risks, neglecting the existence of possible risk interrelationships (Ravulakollu et al., 2018). Risks are not independent, and interconnections often exist between individual risks (Bhalaji et al., 2021; Chopra & Sodhi, 2004; Pellegrino et al., 2024; Qazi & Simsekler, 2022; Qazi et al, 2023).

Understanding how risk factors are connected is indeed crucial for industries because dealing with the main risks – causal risks – can prevent the ripple effects, eliminating the effect of interconnected risks. Ranking of the risk factors will also provide clear guidance for industrial practitioners and researchers in prioritizing their efforts to mitigate the most impactful risks first, ensuring a more resilient supply chain (Bhalaji et al., 2021; Qazi et al, 2023).

There is a risk of overlooking *"causality among risks in a network setting and prioritize risks regarding their network-wide propagation impact"* (Qazi et al., 2023), considering those risks as tail distributions and ignoring critical risks connected to them (Qazi et al., 2023). Therefore, there is a need to develop models that can capture the interdependencies among SCRs (Dubey et al., 2019; Ho et al., 2015; Pellegrino et al., 2024; Qazi & Simsekler, 2022; Qazi et al, 2023). As stated by Smith et al. (2021), most measures focus on individual supply-chain participants and relationships with specific supply-chain partners rather than on the supply chain as a whole, failing to address contextual dynamics of interconnectedness in multi-actor systems (Ravulakollu et al., 2018). Indicators of SCR (stability) offer a broader perspective but are less developed and tend to receive less attention from supply chain managers (Smith et al., 2021).

The presence of risk interdependencies is particularly evident in SCRM. Since a supply chain is, by definition, a system of multiple entities connected through material, information, and monetary flows, supply chain partners are influenced by connected firms and their associated risks (Bugert & Lasch, 2018). Moreover, supply chains are becoming increasingly interdependent due to recent trends such as outsourcing and globalisation (Wei et al., 2010).

Risk interdependency is defined as the existence of a possible precedence relationship between a couple of risks, which affects either the probability of occurrence or the risk impact (Zhang, 2016). Identifying and assessing risk interdependencies are crucial for the management of SCRs for two main reasons. First, the study of risk interrelationships enables the recognition of the hidden influences of certain risks in connection with other risks that may cause substantial damage (Pfohl et al., 2011). Having an overview of the cumulative risk impact is necessary; analysing risks independently prevents us from getting the whole picture of the risks, which may lead to their overall underestimation (Straube et al., 2016). Second, the analysis of risk interdependencies is of crucial importance for the selection of the most appropriate mitigation strategy, since an action that mitigates one risk can, positively or more importantly adversely, affect another (Bhalaji et al., 2021; Chopra & Sodhi, 2004; Qazi & Simsekler, 2022; Qazi et al., 2023).

In the last years, the benefits of the assessment of risk interdependencies have been recognised, and researchers have started employing innovative techniques for this critical task (Choudhary et al., 2023). A recent literature review conducted by Choudhary et al. (2023) identified several SCR assessment techniques, highlighting those that appeared most frequently: Fuzzy sets, Analytic hierarchy processes and their extensions, Analytic network processes, Bayesian networks, Failure mode and effect analysis, Grey theory, Conditional value at risk, Interpretive structural modelling, Delphi technique, TOPSIS, DEMATEL, Mean-variance method, Fault-tree analysis. Similarly, Bugert and Lasch (2018) carried out a literature review aimed at identifying and presenting the available quantitative techniques and one of the criteria used for the evaluation of the selected techniques was the capability to account for risk interdependencies. With this study, the authors identified six main techniques – Petri Nets (PN), System Dynamics (SD), Discrete Event Simulation (DES), Interpretive Structural Modelling (ISM), Input-Output Modelling (IOM), Bayesian Belief Network (BBN) – appropriate for describing and studying risk interdependencies, which are individually detailed below.

- **Petri Nets (PN)** is a graphic technique used for the specification, analysis, and design of discrete event systems (Aloini et al., 2012). More specifically, a PN can be considered a bipartite graph consisting of four different types of elements: places, transitions, arcs, and tokens. Places represent possible states or conditions of the system, while transitions correspond to events that are connected to places through arcs. The actual system state at a certain time is represented by tokens (Bugert & Lasch, 2018).
- **System Dynamics (SD)** is a modelling approach used for analysing complex and dynamic systems. This technique assumes that the structure of a system consists of a set of elements (or variables) that interact with each other through delayed cause-and-effect relationships and information feedback (Bugert & Lasch, 2018).
- **Discrete Event Simulation (DES)** represents the dynamic behaviour of a system as a discrete sequence of events in time. Its high flexibility and ability to model dynamic systems make this technique particularly suitable for supply chain planning problems (Bugert & Lasch, 2018).
- **Interpretive Structural Modelling (ISM)** is a qualitative and interpretive method that generates solutions for complex systems through the structural mapping of complex interconnections of elements (Pfohl et al., 2011). Starting from a complex system characterised

by multiple interdependencies between elements, the ISM methodology can be used to derive a well-structured directed graph (Bugert & Lasch, 2018).

- **Input-output modelling (IOM)** was introduced by Leontief, who used this technique to study the effect of consumption shocks on an interdependent economic system (Bugert & Lasch, 2018). Specifically, Leontief's original model computes the total output production of a sector as the sum of the final demand for that sector and the demand from other sectors. Subsequently, this technique has been extended to assess impacts and manage system risk (Wei et al., 2010).
- **Bayesian Belief Network (BBN)** is a particular typology of Bayesian Networks (BNs). It is a graphical model in the form of a directed acyclic graph in which nodes represent domain variables and arcs between nodes represent probabilistic dependencies (Cooper & Herskovits, 1992). The interdependencies among elements are represented in the form of conditional probabilities. This technique has been applied in a wide range of fields, including SCRM.

2.2 Bayesian Belief Networks

A BN is a *"probabilistic graphical model that provides interpretability of the explored domain by extracting and manifesting dependences, independences, and causal relationships among variables representing the domain"* (Lerner & Malka, 2011).

BNs arise from the concept of Bayesian probability, also called the degree of belief. Its main difference from the concept of classical probability is that it is not necessary to perform repeated trials to compute Bayesian probability. Indeed, instead of being measured, the latter is updated after additional observations according to Bayes' theorem. Specifically, the degree of belief in an event or hypothesis *(H)* is updated, given the background knowledge *(c)* and the additional evidence observed *(E)*, according to the formula:

$$P(H|E,c) = \frac{P(H|c) * P(E|H,c)}{P(E|c)} \tag{1}$$

The concept of belief updating is also called Bayesian inference. Each element of the formula can be defined as in Niedermayer (2008). $P(H|E,c)$ is the posterior probability, that is, the probability of the analysed event after considering the effect of the additional evidence on the background knowledge. $P(H|c)$ is the prior probability to be updated or, more specifically, the probability of H considering c alone. The term $P(E|H,c)$ is called likelihood, and it represents the probability of evidence considering H and c. Finally, the denominator of the formula, $P(E|c)$, represents the probability of evidence assuming c alone. This term is independent of H and can be considered a normalising or scaling factor.

Another important concept in Bayesian mathematics is conditional independence between events. By definition, two events A and B are conditionally independent given a third event C when, given the knowledge that C occurs, the knowledge that B occurs provides no information about the probability of A to occur and the knowledge that A occurs provides no information about the probability of B to occur. Formally:

$$(A \perp\!\!\!\perp B)|C \Leftrightarrow P(A \cap B|C) = P(A|C) \times P(B|C) \tag{2}$$

By introducing the concepts of Bayesian inference and conditional independence, it is possible to provide a mathematical formulation for BNs. A BN for a set of n variables $X = \{x_1, x_2, \dots, x_n\}$ consists of a network structure B_s that encodes a set of conditional independence assertions about variables in X and a set of conditional probability distributions Θ (Heckerman, 2008).

The network structure B_s, is a directed acyclic graph because it does not contain directed cycles. The nodes of B_s are in one-to-one correspondence with the variables within X (Heckerman, 2008). Edges connecting two nodes in B_s show the existence of causal interdependence between the corresponding variables, while a lack of a possible edge represents conditional independence between the corresponding variables (Lerner & Malka, 2011).

The second element of the BN consists of a set of parameters, Θ, including the conditional probability between two variables linked with each arc of B_s and the prior probabilities of the root nodes. Variables belonging to X can be either continuous or discrete, but in most cases, they are assumed to have a limited set of possible states. The conditional probabilities define the relationship between the states of parent and child nodes, and they are usually gathered in specific conditional probability tables.

A topic of interest within the BN literature is how to build the BN. In particular, two main approaches may be adopted to construct a BN:

- *Use belief:* the structure and parameters of the BN are identified through expert judgments, which are also defined as beliefs. For this reason, the obtained graphs are usually known as Bayesian *Belief* Networks (BBNs).
- *Learn the network from data:* The structure and parameters of the BN are retrieved from a dataset of real-world observations.

Both methods present advantages and drawbacks. By adopting a BBN, the interdependencies among variables are conceptually significant since they directly derive from the experts' knowledge; however, results from the usage of the network are inevitably affected by the collected qualitative judgments. On the contrary, learning a BN from data facilitates the identification of statistically relevant interdependencies since they are retrieved from real-world observations. The drawback of this approach is that the found relationships are not necessarily meaningful from a conceptual point of view. In addition, learning the BN from data requires a sufficiently large and reliable dataset to obtain acceptable results and it necessitates a stronger computation effort to be implemented than the BBN option.

BBNs present multiple advantages in terms of the representation and analysis of risks. First, since BBNs are probabilistic tools, they are appropriate for dealing with the uncertain nature of risks (Çıkmak & Ungan, 2022; Sharma & Sharma, 2015). Second, as underlined by Heckerman (2008), BBNs can be used to model the causal relationships between variables, allowing a better understanding of the problem domain and the prediction of the consequences of interventions. This is the main strength of BBNs in the study of risk interdependencies (Çıkmak & Ungan, 2022; Qazi & Simsekler, 2022; Qazi et al, 2023). In addition, BBNs enable the combination of expert judgments and statistical data to model risks. In fact, prior probabilities defined by experts' beliefs can be updated through the rules of Bayesian inference when empirical observations are available (Amundson et al., 2014; Sharma et al., 2022). Moreover, Bayesian inference can be used to determine the probability of risk that may not be observed directly (Çıkmak & Ungan, 2022; Qazi et al., 2018). Sensitivity analyses can be performed to explore different scenarios, allowing for both forward propagation analysis (cause-effect) and backward propagation analysis (effect-cause) (Choudhary et al., 2023; Çıkmak & Ungan, 2022; Qazi et al, 2023). Another advantage arises from the ability of BBNs to represent interdependencies graphically in a way that is easy to understand for humans (Çıkmak & Ungan, 2022; Qazi et al., 2023; Wiegerinck et al., 2013).

Despite these multiple advantages, some limitations should be taken into account during the application of BBNs. A key issue is confidence in experts' beliefs (Amundson et al., 2014). Indeed, the outputs of the model will inevitably be affected by the qualitative inputs provided; therefore, superficial judgments or wrong beliefs may lead to misleading results. Another limitation of this tool is its static nature. BBNs are weak in the portrayal of dynamic features, unlike similar techniques presented in this section (Bugert & Lasch, 2018). To overcome this drawback, BBNs may be combined with more dynamic methods. Amundson et al. (2014) indeed suggested combining BBNs and system dynamics to evaluate long-term policies and run scenario analyses in varying contexts.

2.3 Bayesian Belief Networks in SCRM

In the past decade, many researchers have applied BBNs to SCRM (Badurdeen et al., 2014; Bugert & Lasch, 2018; Garvey et al., 2015; Qazi et al., 2017). Sometimes, academics focus on a specific area of SCRM, such as procurement, transportation, manufacturing, information management, and project management. In other cases, researchers developed a general SCRM framework based on the use of BBNs.

Bugert and Lasch (2018) asserted through their study the advantages of BBNs in identifying and assessing risk interdependencies. Indeed, they stated that *"the inherent strength of the BBN modelling technique is the consideration of risk interdependencies and the possibilities to also take risk propagation into account"* (Bugert & Lasch, 2018). Other researchers have supported this argument (Çıkmak & Ungan, 2022; Qazi & Simsekler, 2022; Qazi et al, 2023). According to Qazi et al. (2018), this technique integrates graph theory tools, thanks to the definition of conditional probabilities, that enable visualising interdependencies and modelling their strengths effectively, which is a characteristic still missing in other graphical tools like PN and ISM. For these reasons, BBNs have gained the growing interest of researchers in modelling SCRMs.

Badurdeen et al. (2014) were among the first to propose an SCRM process entirely based on BBNs. The approach starts with risk identification through the development of a comprehensive SCR taxonomy and an SCR network map, reflecting the interdependencies between all the categories of risk. The goal of the approach is to support the decision maker in identifying the relevant SCRs and their interdependencies for the construction of the BBN structure. In the final stage of the approach, the risk analysis phase, the obtained BBN is explored to gain risk insights.

Garvey et al. (2015) developed an analytical approach to model risk propagation across the supply chain. The supply network is represented through a graph whose nodes are the firms of the supply chain and edges represent the flow of material, information, and money between the organisations. For each node of the supply network, the related SCRs are identified and modelled as binary variables. Each risk variable assumes the value of "0" if it does not occur or the value corresponding to the related cost if it occurs. Once the definition of the BBN is completed, the propagation of each risk node is computed through specific indicators.

Qazi et al. (2017) made use of BBNs to create their SCRM process. The element of newness compared to previous works is that their approach considered and evaluated mitigation strategies. The relevant SCRs and their sources are identified through the FMEA procedure, while experts' judgments are used to elicit the risk interdependencies, the conditional probabilities, and the loss value associated with each risk. Once the BBN has been developed, Bayesian inference is used to compute the expected impact of each SCR, which is a function of its probability to occur and the associated loss. For the risk mitigation stage, two scenarios are considered: in scenario 1, risk mitigation strategies and associated costs are not pre-defined; in scenario 2, the strategies and their costs are already established as a result of the FMEA procedure. In scenario 1, risks are prioritized using a metric derived from Game Theory, the Shapley Value, to identify the most critical SCRs to be treated. Under scenario 2, the optimal set of mitigation actions is selected according to a specific objective function and under a budget constraint.

The following study of Qazi et al. (2018) is considered particularly relevant as introduced an innovative combination of BBNs and expected utility theory to address the complex, interconnected nature of SCRs. The novelty of the study lies in its ability to capture probabilistic relationships between various risk events using BBNs, highlighting the interdependencies and propagation of risks within a supply chain network. The integration of an expected utility framework further enhances the model by evaluating and comparing risk mitigation strategies based on both the probabilities of risk events and the utilities associated with different outcomes, thereby providing a decision support tool for identifying the most effective risk mitigation strategies.

Furthermore, Laurila-Pant et al. (2019) applied the BBN approach to incorporate stakeholders' views into environmental decision-support processes. The approach quantifies and visualizes variability in stakeholder values, linking this information to a larger decision-analytic influence diagram.

Another work, conducted by Liu et al. (2021), proposed a robust Dynamic Bayesian Network (DBN) approach to estimate disruption risks propagating along the supply chain. The DBN approach focuses on worst-case scenarios and uses nonlinear programming and simulated annealing algorithms to handle data scarcity and estimate disruption risks. The robust DBN approach addresses the ripple effect in supply chains, providing a novel method for disruption risk assessment in scenarios with limited data.

The study of Hosseini & Ivanov (2022) focused on disruptions, in particular the COVID-19 pandemic, to assess the impact on supply chains and their performance. This model consists of three layers – disruption triggers, risk events, and consequences – and enables the estimation of the probability of outcomes on identified triggers and events. By capturing the causal relationships between these elements, it is possible to achieve a more detailed understanding of disruption impacts compared to traditional models.

According to the recent literature on BBNs, the study of Qazi et al. (2018) is particularly significant for this research, as it can be beneficial to evaluate risk interdependence and recurrent risks using the expected utility theory. Given the high relevance of this article, an independent section (*2.3.1*) is inserted to present it in-depth.

2.3.1 The considered reference BBN approach for SCRM

The study of Qazi et al. (2018) is an example of a general SCRM approach. Multiple contributions make this article relevant to the analysed literature. Indeed, this paper not only describes a complete SCRM process accounting for the interdependencies between SCRs, but it also introduces a Weighted Net Evaluation (WNE) for risk mitigation aimed at managing the compromise between the efficacy of potential mitigation strategies and their costs, considering the decision maker's risk appetite. In particular, the efficacy of the mitigation strategies is evaluated through the expected utility theory, which is a measure of the risk level characterising the BBN.

The approach proposed by Qazi et al. (2018) follows the major steps below:

- context definition;
- risk identification;
- risk analysis;
- risk evaluation and treatment;
- risk monitoring and review.

The approach developed by Qazi et al. (2018) focuses on group sessions to identify risks and develop a causal network. In particular, the informants are asked to link each performance measure with the corresponding risks that are in turn linked to causal factors. Subsequently, subject experts are interviewed to define the strength of risk interdependencies, that is, the conditional probabilities.

The resulting BBN consists of N interdependent binary risks, denoted as R_j with $j \in \{1, \dots, N\}$, and M performance measures, denoted as m_l with $l \in \{1, \dots, M\}$, and $M < N$. For every combination of performance measure values, a state, $s_i \in \{good, bad\}^M$, is defined. In total, there are $I = 2^M$ states that the network can assume.

The next step is the definition of the utility function, $u: \{good, bad\}^M \rightarrow [0,1]$. In particular, experts have to associate each possible state of the network with a utility value on the unit interval. In this way, the expected utility of the network can be computed as:

$$EU = \sum_{i=1}^{I} p_i u(s_i) \tag{3}$$

where p_i is the probability that the network assumes the state s_i.

Once the network structure and parameters have been defined, the risk mitigation stage can start. First, decision makers must define a set of mitigation actions, denoted as $a \in \{1, \dots, A\}$, that can reduce the probability of occurrence of some risks. These actions can be combined in any way to form a mitigation strategy denoted as σ_k. In total, there are $K = 2^A$ mitigation strategies available. At this stage, the WNE score of a mitigation strategy is computed. This score function aims to manage the trade-off between the efficacy of a mitigation strategy, considering the decision maker's risk propensity, and its cost of implementation.

$$WNE(\sigma_k) = (1-\alpha)\sum_{i=1}^{I} p_i(\sigma_k)u(s_i) + \alpha v(C_k) \tag{4}$$

where $p_i(\sigma_k)$ is the new probability of the state s_i after σ_k is implemented, $v(C_k)$ is the utility value associated with the cost of implementation, C_k, and α defines the level of risk propensity of the decision maker. In particular, if $\alpha < 0.5$, the decision maker is reluctant to take risks (*risk-averse*), while if $\alpha > 0.5$, the decision maker tends to take risks (*risk-taker*).

If $\alpha = 0.5$, the decision maker is *risk-neutral*. Having defined how the outcome of the implemented mitigation strategies is evaluated, the problem of strategy selection can be formulated as:

$$max_{(\sigma_k \epsilon K)}\, WNE(\sigma_k)\; s.t.\, C_k \leq \bar{C} \tag{5}$$

where $\bar{C}$ is the budget available for strategy implementation.

During the risk monitoring and review phase, a focus group session is conducted to communicate the results of the process. As SCRM is a continuous process, the approach is repetitively applied by using the information gained during previous iterations.

3 Theoretical background

The analysis of the state of the art highlighted the key role of BBNs in an effective assessment of the interdependencies among SCRs. The contributions presented above indicate that the study of Qazi et al. (2018) seems to be a significant application of BBN to SCRM.

Qazi et al. (2018) used probability-impact matrices to evaluate the criticality level of risks and risk sources of the BBN to support decision makers in selecting optimal strategies. For the development of such matrices, risk likelihood is assumed to be the posterior probability of the worst state of each risk, which is obtained through Bayesian inference. However, the assessment of risk impact is much more complex. The authors have approximated the risk impact with the percentage decrease of expected utility obtained by instantiating the risk node in its worst state and taking as a reference point the average case:

$$Impact\ (R_i) = \frac{Expected\ Utility_{R_i=avg\ case} - Expected\ Utility_{R_i=worst\ case}}{Expected\ Utility_{R_i=avg\ case}} \qquad (6)$$

Qazi et al. (2018) study set the reference point on the average expected utility, equation (6). The average case seems reasonable at first glance since it can be considered a proxy of the decision maker's expectations (or probabilistic beliefs) about future outcomes. However, some risk types do not fit well with this approach: recurrent risks are a clear example. HF risks significantly affect the expectations and risk aversion of decision makers (Rivers & Arvai, 2007). Decision makers tend to mitigate LF-HI risks while accepting recurrent minor disturbances because they are accustomed to those circumstances, which increases their risk aversion. Therefore, the average case as a reference point for recurrent risks considers a scenario where risks are kept frequent, and a low expected utility is accepted. This implies that the expected utility in the average case is relatively closer to the worst case rather than to the best one, that is when risk is completely avoided or mitigated, thus keeping the impact (R_i) indicator small. An accurate assessment of risk impact is thus crucial, according to the Qazi et al. (2018) approach, to support decision makers in selecting the optimal strategies for risk mitigation, which is by the way a major goal of many studies on SCRM.

The relationship between expected utility and a selected reference point is not a new topic in the literature. Kahneman and Tversky (1979) developed an innovative theory, the *prospect theory*, an alternative to the *expected utility theory* for decision making under risk. A decision maker faces risk when they can associate probabilities to the possible feature outcomes; whereas uncertainty stands for a situation where the probabilities estimation is not workable. Decision making under risk represents a choice between prospects. A prospect $(x_1, p_1; x_2, p_2; \ldots; x_n, p_n)$ yields an outcome x_i with a probability p_i, where $p_1 + p_2 + \cdots + p_n = 1$, the expected utility of such a prospect can be computed as:

$$EU(x_1, p_1; x_2, p_2; \ldots; x_n, p_n) = p_1 u(x_1) + p_2 u(x_2) + \cdots + p_n u(x_n) \qquad (7)$$

where $u(x_i)$ defines the level of utility associated with outcome x_i.

According to the expected utility theory, a purely rational decision maker should always select the prospect corresponding to the maximum expected utility. However, Kahneman and Tversky (1979) observed through empirical experiments that this is not always true. For this reason, they formulated the prospect theory.

The main result of the prospect theory was the development of a new utility function, which, according to the authors, should approximate the preferences of the decision makers under risky conditions better than the expected utility theory. One of the features of this new utility function is that it is defined on deviations from a reference point. This characteristic derives from the observation that people are likely to evaluate outcomes in terms of gains and losses rather than as final states of wealth. A consequence of this feature is that a shift in the reference point can change the utility perceived by the decision maker. In the original formulation of the prospect theory, the reference point corresponded to the status quo, that is, the current level of the decision maker's wealth. However, Kőszegi and Rabin (2006) proposed a new version of the prospect theory, in which the reference point was associated with the expectations of the decision maker. The authors defined expectations as the probabilistic beliefs that the decision maker held in the recent past about future outcomes. Expectations depend on the notion of personal equilibrium, which is a condition when a person correctly predicts the environment they face and their reactions to this environment.

In many cases, the status quo and expectations are interpreted as equal since people usually expect the status quo to be maintained in the future. However, there are situations in which these perspectives differ and the status quo, as a reference, seems to be inappropriate (Kőszegi & Rabin, 2006). Workers, for instance, tend to perceive a wage reduction as a loss, even if it does not cause changes to their status quo. Indeed, the salary reduction leads to a reduction of the expected gain rather than a real loss of the current workers' welfare. In this case, the loss perception is justified only when expectations are used as a reference point.

Resuming the above discussion on recurrent risks and chronic losses, this is especially true. In such a context, individual perceptions play a key role in the prediction of expected outcomes (Ravulakollu et al., 2018). Humans consider both logical data-driven decisions and intuitive quick decisions. Therefore, their perception of risk is influenced by their emotions towards potential outcomes, especially their dread or fear of unknown outcomes (Slovic et al., 2004).

Rivers and Arvai (2007) made an important contribution to this topic by studying the impact of chronic losses on expectations in the context of the prospect theory. The authors carried out an experiment comprising three groups of respondents. One group, chronic losers, was exposed to chronic financial losses as part of a controlled, multi-round gambling simulation. Groups two and three were exposed to chronic wins and random outcomes, respectively, as part of the same gambling simulation. The results of this study showed that subjects who have suffered recurrent failures tended to lower their expectations and increase their level of loss aversion.

4. Methodology

Taking the stand from the existing knowledge on BBNs for SCRM, this work advocates a change in existing approaches to properly evaluate recurrent risks, which determine chronic losses and are often underestimated due to the decision maker's expectations (Rivers & Arvai, 2007). We propose a novel approach to assess the risk impact on different scenarios when considering recurrent risks and their interdependence with other risks.

4.1 Proposed SCRM approach

The proposed research approach is centred on the comparison of two distinct approaches for the evaluation of risk impact within the general SCRM approach based on the use of BBNs developed by Qazi et al. (2018).

The approach suggested by Qazi et al. (2018), reported in equation (6), at first glance, seems reasonable because it reflects the willingness to compare the worst case, in which risk occurrence is certain, with the average or expected case. However, such an approximation could determine potential distortion when treating recurrent risks. As mentioned earlier, using the average case as the reference point for the computation of the decrease in expected utility will likely lead to an underestimation of the impact of HF risks.

The approach proposed in this work that overcomes this drawback considers the percentage decrease of utility from the best case, that is when the risk does not occur with certainty:

$$Impact\ (R_i) = \frac{Expected\ Utility_{R_i=Best\ case} - Expected\ Utility_{R_i=Worst\ case}}{Expected\ Utility_{R_i=Best\ case}} \tag{8}$$

To avoid any misunderstanding in the following pages, the Qazi et al. (2018) impact measure (equation (6)) will be labelled as the *benchmark* approach, while the above impact measure (equation (8)) will be indicated as the *proposed* approach. The difference between such methods involves the setting of the reference point for the computation of the expected loss of utility. Whilst the *benchmark* approach uses the expected utility of the average case, the *proposed* approach uses the best case for the reference point. Although the difference between the two approaches could seem minimal, however conceptually the difference is significant because it stems from the limitations of BBNs by reducing the biases introduced in the process by decision makers, who are people and their arguments, even though reasoned, are mostly based on their personal experience (Kőszegi & Rabin, 2006). Therefore, the main novelty of this work is mainly conceptual rather than computational, and in the results (Section 5), it will become clear.

To effectively compare the *benchmark* and *proposed* approaches, the BBN developed by Qazi et al. (2018) in their case study was used. Therefore, the two approaches were compared based on the same case study to verify whether the adoption of these distinct approaches can lead to different results regarding the evaluation of risk impact, especially for recurrent SCRs. This enabled to directly compare the impact of different risks and identify those mostly underestimated by the *benchmark* approach.

4.2 The sample

The selected company is called Aero, a leading global supplier of products, solutions, and services like rolling bearings, seals, mechatronics, services, and lubrification systems. Aero has 120 manufacturing units, operates in 29 countries, and serves a wide range of industries such as automotive, marine, aerospace, and renewable energy.

The BBN developed for Aero is constituted of 50 nodes, including the node for the computation of the expected utility of the network and the five performance variables: quality, timeliness, market share, profit, and sustainability.

Figure 1 shows the full risk network, together with the interrelationships between mitigation strategies and risk nodes. The mitigation strategies were evaluated during the risk treatment stage, considering different levels of risk propensity and budget constraints.

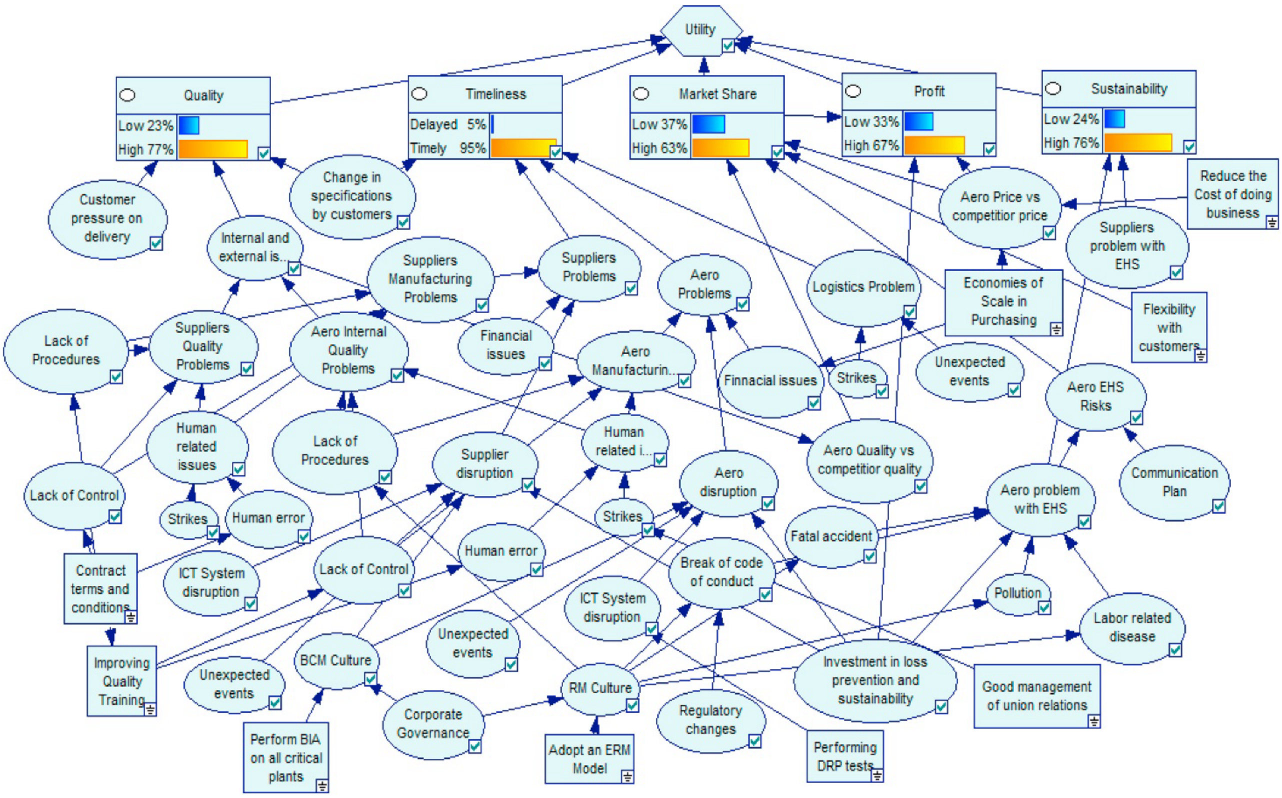

Figure 1: BBN of the Aero case: the network of interacting risks, risk sources and potential strategies *[retrieved from Qazi et al. (2018)]*.

4.3 The BBN structure

The GenLe Modeler software (Bayes Fusion LLC, 2020) was applied to rebuild the Bayesian structure, starting with the information provided by the paper of Qazi et al. (2018). The GenLe Modeler is a tool for artificial intelligence modelling and machine learning with BNs and other types of graphical probabilistic models (Bayes Fusion LLC, 2020). The interface of this software is very intuitive and user-friendly. It allows the exploitation of all the features of BNs from the update of probabilities through Bayesian inference to the development of sensitivity and what-if analyses. Among the functionalities of this software, there is the possibility of learning the BN from a dataset given as input to a specific learning algorithm.

The unavailability of the conditional probability tables complicated the rebuilding of the original BBN. The authors were contacted and requested to share the complete dataset, but they replied that this was not possible because of confidentiality.

To provide an estimation for missing parameters due to the unavailability of conditional probabilities, it was necessary to test different datasets. A structured approach was followed for such a task, consisting of four steps:

- defining the datasets to be tested;
- testing the datasets by computing the posterior probability of each node;
- computing the absolute deviation for each node;
- selecting the dataset minimizing the Mean Absolute Deviation (MAD).

Nine different datasets were tested to identify the one that best approximated the missing parameters. The best dataset is available under request. Once the BBN construction was completed (Figure 1), the probability and the two impact measures of each node of the network were computed.

Following the example of Qazi et al. (2018), nodes were positioned in the probability-impact matrix to evaluate their level of criticality. However, to get a significant comparison among risks, the nodes were divided according to two different classifications.

- By type: distinguishing between parent, intermediate, and child nodes.
- By level: according to the hierarchical position of the node within the BBN. Specifically, performance variables (i.e., *quality*, *timeliness*, *market share*, *profit*, and *sustainability*) belong to Level 0, whereas nodes directly connected with them are gathered in Level 1. Level 2 nodes are those linked with Level 1 variables and Level 3 nodes are parents of Level 2 nodes.

Once the BBN was implemented in GenLe (Bayes Fusion LLC, 2020), all the nodes were categorized, and the two measures of risk impact (*benchmark* and *proposed* approach) were computed for all the variables of the BBN. All types of risks (HF-HI, LF-HI, HF-LI, LF-LI) were included in the Aero case and their impact, for the *benchmark* and *proposed* approach as well, was assessed to detect whether there were differences between risks according to their classification, by type and by level.

5 Results

The *proposed* approach proved to be effective in properly evaluating chronic losses without introducing biases to the other variables (risks). The results of this analysis are reported in Table 1, where the column *Delta* represents the difference between the risk impact computed with the *proposed* approach and that obtained using the *benchmark* approach.

Table 1: Resulting differences between the *benchmark* and *proposed* approaches.

Node Name	Node Identifier	Type	Level	Probability of the worst state	Impact (*Benchmark*)	Impact (*Proposed*)	***Delta***
Corporate Governance	N1	Parent	3	25.0%	1.57%	2.08%	***0.51%***
RM Culture	N2	Intermediate	3	39.0%	1.89%	3.04%	***1.16%***
Regulatory Changes	N3	Parent	3	10.0%	0.30%	0.34%	***0.04%***
Unexpected Events (Supplier)	N4	Parent	3	10.0%	0.06%	0.07%	***0.02%***
Lack of Control (Aero)	N5	Parent	3	5.0%	2.35%	2.46%	***0.11%***
BCM Culture	N6	Intermediate	3	61.0%	0.04%	0.09%	***0.06%***
Unexpected Events (Aero)	N7	Parent	3	10.0%	0.07%	0.07%	***0.00%***
ICT System Disruption (Aero)	N8	Parent	3	5.0%	0.11%	0.11%	***0.00%***
Investment in Loss Prevention and Sustainability	N9	Parent	1	20.0%	6.76%	8.30%	***1.54%***
Break of Code of Conduct	N10	Intermediate	2	29.8%	2.43%	3.42%	***0.99%***
ICT system Disruption (Supplier)	N11	Parent	3	5.0%	0.07%	0.07%	***0.00%***
Strikes (Supplier)	N12	Parent	3	10.0%	0.21%	0.22%	***0.02%***
Human Error (Supplier)	N13	Parent	3	10.0%	0.21%	0.22%	***0.02%***
Human Error (Aero)	N14	Parent	3	5.0%	0.41%	0.43%	***0.02%***
Strikes (Aero)	N15	Parent	3	5.0%	0.41%	0.43%	***0.02%***
Aero Disruption	N16	Intermediate	2	11.4%	1.83%	2.07%	***0.24%***
Fatal Accident	N17	Intermediate	2	4.0%	3.16%	3.28%	***0.13%***
Pollution	N18	Intermediate	2	12.0%	2.50%	2.83%	***0.33%***
Labour Related Disease	N19	Intermediate	2	7.0%	2.37%	2.53%	***0.16%***
Lack of Control (Supplier)	N20	Parent	3	10.0%	2.00%	2.22%	***0.22%***
Human Related Issues (Supplier)	N21	Intermediate	3	23.2%	0.99%	1.28%	***0.29%***
Lack of Procedures (Aero)	N22	Intermediate	3	39.0%	1.83%	2.97%	***1.14%***
Supplier Disruption	N23	Intermediate	2	11.4%	1.62%	1.83%	***0.20%***
Human Related Issues (Aero)	N24	Intermediate	3	12.5%	1.49%	1.71%	***0.22%***
Financial Issues (Aero)	N25	Parent	2	1.0%	0.30%	0.30%	***0.00%***
Aero Quality vs. Competitors Quality	N26	Intermediate	1	45.9%	12.45%	20.82%	***8.37%***
Aero Problem with EHS	N27	Intermediate	1	36.7%	6.09%	9.29%	***3.20%***
Communication Plan	N28	Parent	2	20.0%	0.56%	0.69%	***0.13%***

Lack of Procedures (Supplier)	N29	Parent	3	10.0%	1.21%	1.34%	***0.13%***
Supplier Quality Problem	N30	Intermediate	2	21.1%	6.89%	8.58%	***1.69%***
Aero Internal Quality Problem	N31	Intermediate	2	22.2%	7.06%	8.89%	***1.84%***
Suppliers Manufacturing Problem	N32	Intermediate	2	16.4%	1.18%	1.40%	***0.22%***
Financial Issues (Supplier)	N33	Parent	2	10.0%	0.17%	0.19%	***0.02%***
Aero Manufacturing Problem	N34	Intermediate	2	16.3%	1.77%	2.10%	***0.33%***
Strikes (Logistic)	N35	Parent	2	5.0%	0.34%	0.35%	***0.02%***
Unexpected Events (Logistic)	N36	Parent	2	5.0%	1.12%	1.18%	***0.06%***
Aero EHS Risks	N37	Intermediate	1	29.4%	7.02%	9.67%	***2.65%***
Customer Pressure on Delivery	N38	Parent	1	50.0%	2.89%	5.63%	***2.73%***
Internal and External Issues	N39	Intermediate	1	39.7%	16.02%	24.03%	***8.01%***
Change in specification by customers	N40	Parent	1	20.0%	6.22%	7.65%	***1.43%***
Supplier Problem	N41	Intermediate	1	13.0%	2.18%	2.49%	***0.31%***
Aero Problem	N42	Intermediate	1	12.1%	3.22%	3.65%	***0.43%***
Logistic Problem	N43	Intermediate	1	12.3%	2.89%	3.29%	***0.40%***
Aero Price vs. Competitors Price	N44	Parent	1	90.0%	2.60%	20.99%	***18.40%***
Supplier Problem with EHS	N45	Parent	1	10.0%	4.18%	4.63%	***0.45%***
Quality	N46	Child	0	33.8%	39.23%	49.36%	***10.14%***
Timeliness	N47	Child	0	7.0%	19.96%	21.14%	***1.18%***
Market Share	N48	Child	0	70.1%	15.74%	38.47%	***22.73%***
Profit	N49	Child	0	59.9%	19.72%	37.99%	***18.27%***
Sustainability	N50	Child	0	34.0%	11.18%	16.03%	***4.84%***

The first fact noticeable from Table 1 is that the *Delta* value (last column) is, for construction, higher than or equal to zero for all the nodes of the network. This means that the risk impact computed with the *benchmark* approach is always lower than or equal to the impact measured by the *proposed* approach. This fact is a consequence of the different estimations of the reference point. Indeed, the reference point set by the *proposed* approach (i.e., the expected utility when the node is instantiated in its best state) is higher than or equal to the reference assumed by the *benchmark* approach (i.e., the expected utility of the average case).

At this stage, the next step was to understand the risks that were mostly underestimated and whether there was a correlation between risk underestimation and the frequency of their occurrence. Looking at the numerical results of the analysis, it was decided to correlate the *Delta* value with the *Node Level* and the *Probability of the worst state*. The Pearson correlation coefficient was used to evaluate the correlation between these variables (Table 2).

Table 2: Resulting in Pearson correlation coefficients.

	Probability of the worst state	Level
Delta	0.79716	−0.60411

The correlation analysis has shown that there is a strong positive correlation between *Delta* and the *Probability of the worst state* since their Pearson correlation coefficient is equal to 0.797, thus higher than 0.7, while the correlation between *Delta* and *Node Level* is only moderate (between 0.3 and 0.7) since the absolute value of these variables' coefficient is equal to 0.604.

Therefore, we can state that the difference between the *benchmark* and *proposed* impact measures increases as the risk likelihood increases, and it is more significant for nodes belonging to lower levels, i.e., closer to the nodes for the computation of the expected utility of the network.

By analysing all the different nodes in Table 1, it is noticeable that the impact of the node *Aero Price vs. Competitors Price* (N44) is heavily underestimated by the *benchmark* approach. Indeed, the *Delta* value for this node is 18.40%, which is equivalent to around 708% of the risk impact computed using the *benchmark* approach. This fact shows evidence of the previous considerations on the relationship between *Delta*, *Probability of the worst state*, and *Level*. *Aero Price vs. Competitors Price* is indeed a recurrent risk (the *Probability of the worst state* is equal to 90%) and it belongs to Level 1.

6 Discussion

The results of the analysis described above confirmed the theoretical intuitions presented in the previous sections. The adoption of the *benchmark* approach may lead to an underestimation of the impact of some risks. In particular, the results of this work have demonstrated that HF risks, located close to the expected utility function of the network, are more likely to be underestimated.

These insights confirmed the link between recurrent risks and the concept of chronic losses studied by Rivers and Arvai (2007). Indeed, it was shown that when using the *benchmark* approach, recurrent risks have the effect of lowering the expectation of the decision makers, which reduces the perception of their impact (loss).

Because of the result difference between the *benchmark* and *proposed* approaches, the considerations of the decision makers and the consequent selection of mitigation strategies are significantly affected by the method used to assess risk impact. This drawback is noticeable by applying the probability-impact matrix to evaluate the criticality of risks.

Figure 2 compares the probability-impact matrices, including all the parent nodes, obtained using the *benchmark* and the *proposed* approaches. When using the approach suggested by Qazi et al. (2018), N44 (*Aero Price vs. Competitors Price*) does not seem critical. Indeed, despite being the risk with the highest likelihood of occurrence, its impact is lighter than other risks such as N9 (*Investment in Loss Prevention and Sustainability*) and N40 (*Changes in Specification by Customers*). The result completely changes if the *proposed* approach is adopted. N44 becomes the most critical parent node of the network in terms of both impact and likelihood.

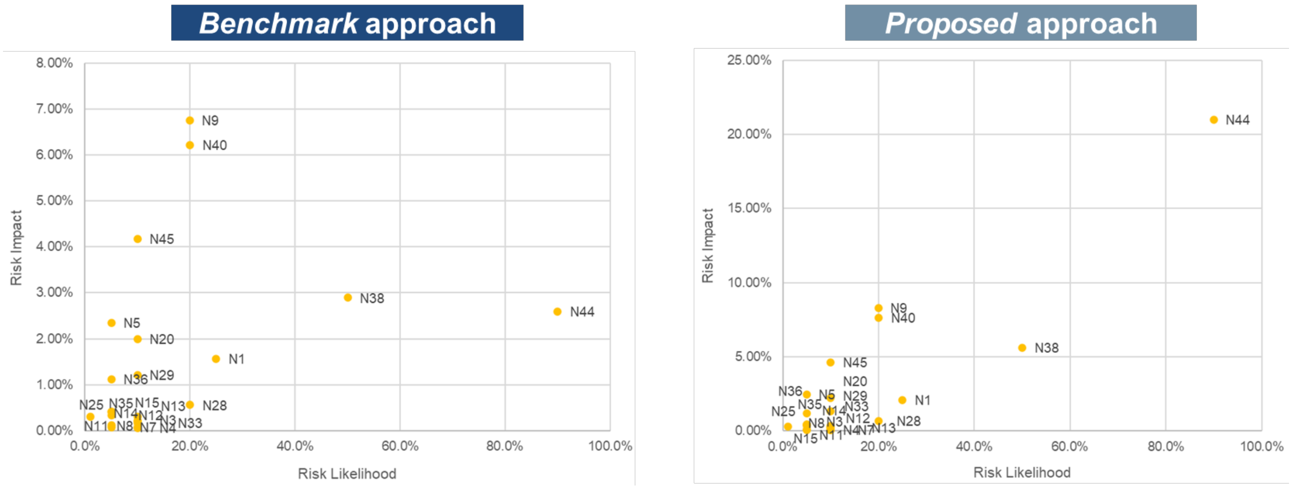

Figure 2. Probability-impact matrices for parent nodes using the *benchmark* and *proposed* approaches.

A similar discrepancy in results may be found by adopting the probability-impact matrices to compare the positioning of nodes belonging to Level 1, as shown in Figure 3. By using the *benchmark* approach, N44 is one of the nodes with the smallest impact within this level. On the contrary, by adopting the *proposed* approach, it is noticeable that the impact of this node becomes one of the highest.

In the comparison of these matrices, it is important to highlight the positioning of N26 (*Aero Quality vs. Competitors Quality*) and N39 (*Internal and External Issues*). These nodes appear to be critical in both matrices despite the change in risk impact measurement because of their high *Delta* values: 8.37% for N26 and 8.01% for N39. This example clearly shows that the *benchmark* and the *proposed* approaches do not always yield different results.

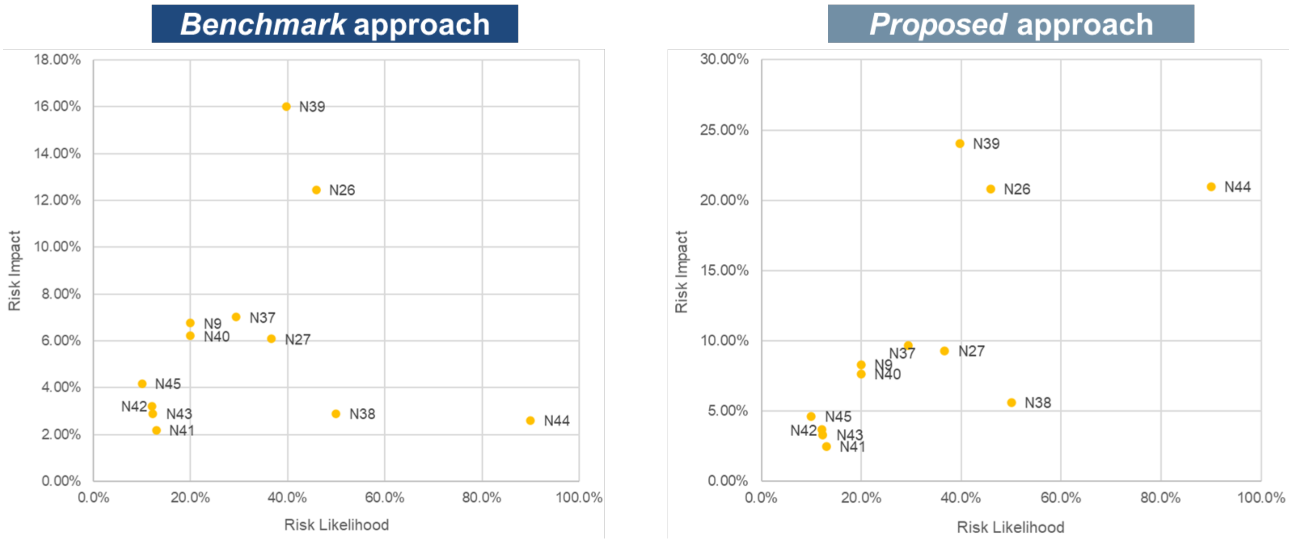

Figure 3. Probability-impact matrices for Level 1 nodes using the *benchmark* and *proposed* approaches.

These comparisons show that adopting the *benchmark* approach to develop the probability-impact matrix may lead managers to inappropriate mitigation decisions. They may decide to accept an HF-LI risk to save resources for treating other disturbances when, in reality, the mitigation of such risks would lead to a more significant improvement in firm performance.

Most times, a vicious cycle is created: non-mitigated recurrent risks lower the expectations of the decision makers, which reduces the perception of their chronic loss and encourages managers to continue accepting them. As admitted by Kőszegi and Rabin (2006), an actual definition of expectations does not exist; expectations are based on the concept of personal equilibrium, which is a subjective and emotional condition of the human decision maker. This means that misleading beliefs can bring huge biases to the evaluation of risks and the selection of mitigation strategies. The graphical representation of this misleading cycle is reported in Figure 4.

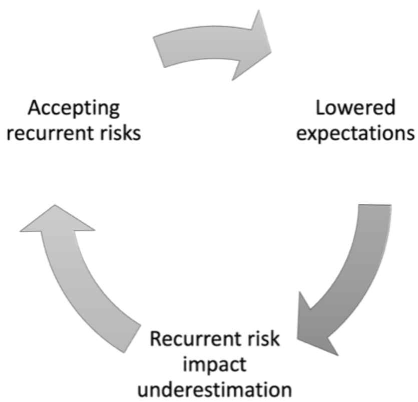

Figure 4. Vicious cycle deriving from the use of the *benchmark* approach.

The risk impact measurement approach suggested by Qazi et al. (2018), despite being coherent with the concept of expectation, is not completely reliable because it poses the problem of chronic loss underestimation and the vicious cycle originating therefrom. Therefore, the adoption of the *proposed* approach should be considered. Setting the reference point on the expected utility of the best case circumvents the problem of lowered expectations and breaks the vicious cycle described above.

7 Conclusions

The present work starts by analysing the state of the art of SCRM and risk interdependencies. Then, it focuses on recurrent risks characterised by a high impact over time, which determine chronic losses. This work mainly contributes to raising attention to chronic losses, still often underestimated by the top management, and proposing an approach for the evaluation of their impact when it comes to interdependent risks.

Proper methodologies for risk identification first and then risk quantification are still limited. This work takes inspiration from the existing approach of Qazi et al. (2018) of BBNs for risk interdependencies in SCRM to consider, not underestimate, recurrent risks and keep properly monitoring the others as well. Qazi et al. (2018) approach is considered particularly relevant as introduced an innovative combination of BBNs and expected utility theory to address the complex, interconnected nature of SCRs. The key role of expected utility theory within this approach emphasizes the importance of the expectations of the decision makers within the risk assessment (Choudhary et al. 2023), hence it can be beneficial to evaluate risk interdependence and recurrent risks. Theoretical insights from works related to such a theory suggest that expectations reflecting a homeostatic attitude towards SCRM can lead to the underestimation of the impact of chronic losses (Rivers & Arvai, 2007). Slovic et al. (2004) highlighted that people's perception of risk is influenced by their emotions towards potential outcomes, especially their dread or fear of unknown outcomes. Therefore, recurrent risks are often given for granted inside companies, and it is necessary to raise awareness of this issue, so thereby proper mitigation strategies can be then implemented and take into account risk interdependencies and subjective perceptions of decision makers.

This work moves from current applications of BBNs by proposing a reliable approach for measuring risk impact and highlighting the hidden effects of chronic losses that affect firm performance. Indeed, the initially considered approach from Qazi et al. (2018), the *benchmark* approach, relies on the expectations of decision-makers, but it does not consider their homeostatic attitude towards SCRM, which, especially for recurrent risks, may lead to the underestimation of the risk impact. Because of this underestimation, a vicious cycle starts, that is, recurrent risks are not mitigated because they are not perceived as critical, the constant presence of HF risks lowers the expectations of the decision makers, and consequently, their impact appears even more insignificant. The adoption of the *proposed* approach can break this misleading cycle and prevent the persistent underestimation of chronic losses.

7.1 Theoretical contributions

This work contributes to the literature in several ways.

The main contribution is given by the *proposed* novel approach, which assesses the risk impact of interdependent risks by evaluating more accurately recurrent risks often underestimated due to the decision maker's expectations (Rivers & Arvai, 2007). Therefore, this work introduces an approach properly considering risk interdependences and chronic losses and reducing the potential biases introduced by decision makers.

As a consequence, this work highlights the importance of studying causal interdependencies and emphasizes the need to consider not only HF-HI and LF-HI risks but also recurrent, seemingly minor, risks in SCRM processes. The results of this work prove that the impact of recurrent risks, which determine chronic losses, may be underestimated due to the decision maker's homeostatic attitude, as their expectations are lowered.

In addition, this work applies the *prospect theory* and tested it in the SCRM environment to better assess the impact of recurrent risks. Therefore, this work by comparing the *benchmark* with the *proposed* approach, is implicitly comparing two theories – *expected utility theory* and *prospect theory* – and showing that depending on the contexts one can fit better than the other.

7.2 Managerial contributions

Several implications can be derived from this work to the advantage of practitioners and managers.

First, this work recommends the use of BBNs as a quantitative method for effective risk assessment considering risk interdependencies. By using such a tool, practitioners can obtain a full understanding of the risk domain and conduct useful analyses.

Second, the research approach proposed by this work, besides offering a reliable measure of risk impact, has shown how the impact of recurrent risks can be concealed by the expectations of decision makers, reflecting their homeostatic attitude. In recent years, practitioners have directed their attention towards HF-HI and LF-HI risks, since SCRM has often been described as a process of building a firm's capabilities for dealing with large disruptions that could affect the flows of the supply chain (Bode & Macdonald, 2017). However, this work has remarked that even recurrent and apparently minor risks may have a decisive impact on company performance. Hopefully, after reading these pages, more managers will turn their attention to chronic disturbances and their hidden effects on firm performance.

7.3 Limitations and Future Research

The limitations of the present work suggest the direction for future research based on this work.

This work has focused on the use of BBNs for the representation and analysis of risk interdependencies. It may be interesting to examine how the larger category of BNs can be used for this scope. Future research could try to retrieve the risk network structure from empirical data by applying one of the multiple learning algorithms available for BN construction. Indeed, such an approach removes one of the major limitations of BBNs: the confidence in experts' beliefs. However, as mentioned above, the interdependencies statistically detected through the learning algorithms are not necessarily meaningful from a conceptual viewpoint. Alternatively, future researchers can combine these approaches through the tuning process to obtain a risk network which is statistically and conceptually meaningful. Another limitation of BBNs is that they are weak in the portrayal of dynamic features (Bugert & Lasch, 2018), and as said before, to overcome this drawback, BBNs may be combined with more dynamic methods.

The second main limitation of the present work is the methodology applied to set the conditional probability tables used by Qazi et al. (2018) for the Aero case study that were unavailable from the original paper. Hence, a test for missing parameters was carried out thus introducing a potential bias in data evaluation. It would be valuable to replicate the comparison between the *benchmark* and *proposed* approaches using the original dataset of the case study.

Finally, the same research approach may be applied to a completely different case study to further validate the obtained results.

Declaration of Competing Interest

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