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AN EFFICIENT STOPPING RULE FOR MITIGATING RISK FACTORS: APPLICATIONS IN PHARMACEUTICAL AND GENERALIZED GREEN SUPPLY CHAINS

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Abstract: *Risks in supply chains are first identified and then prioritized based on their probability of occurrence and their impact. Attempts to mitigate risks in the absence of complete and accurate information about their likelihood and impact may constitute a significant waste of resources. Since the resources available for risk management are usually limited, firms need to know how to allocate these funds appropriately. That is, a strategy is required to determine which risks are a priority in terms of acquiring complete and accurate information. We develop a model that incorporates two conflicting terms to address this issue. The first, captured by entropy, measures the resources wasted due to risk factors for which there is inaccurate information about the probability of occurrence and impact. The second is the cost associated with the efforts expended in collecting accurate information about risk factors. To solve the model, we propose a stopping-rule algorithm. Its efficiency is verified using data gathered from a real-world pharmaceutical and generalized green supply chains. Numerous computerized experiments show that the stopping-rule algorithm prevails over the widely used risk-management Pareto rule, and that the algorithm is able to achieve the optimal solution in 94% of investigated cases.*

Key words: *Shannon entropy; Pharmaceutical supply chain; Generalized green supply chain; Supply chain risk management.*

1. Introduction

1.1. Supply-chain risks

This paper is concerned with risk management in supply chains. A supply chain (SC) is a widely used term that refers to an integrated network of entities, beginning with the initial supplier and ending with the customer, that aims to effectively and

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efficiently synchronize demand and supply across those entities, while providing value to all stakeholders (Lawrence et al., 2019). Typical examples of supply chains include the web, multimedia communication networks, healthcare, and large-scale technological projects (Herbon et al., 2012; Laumanns & Lefeber, 2006).

Supply-chain risk management (SCRM) is an important tool when faced with potential disruption, and can help reduce the likelihood and severity of risk scenarios occurring in SCs. In rapidly changing and unpredictable working environments, supply chains are exposed to various internal and external risks that may have a substantial impact on their operation, causing financial or reputational damage. For instance, internal risks (e.g., poor stock visibility, inventory shortages) may increase operational costs and cause lost sales. External threats (e.g., boycotts) may cause delays in planned deliveries, thereby reducing customer satisfaction and inducing reputational damage.

One example of a supply-chain risk is unexpectedly high inventory costs, which can occur due to obsolescence. Financial losses can also arise for other reasons, e.g., through the need to rework stock or due to the penalties incurred for the non-delivery of goods or due to stock-outs. An example of the latter was the crisis that affected Ericsson in 2000, where a fire that took place at the firm's sole supplier of microchips immediately disrupted the entire material supply, with estimated losses of USD 400 million according to the T28 model (Norrman & Jansson, 2004). The flood in Chennai, India in 2015 resulted in an economic loss of US $2.2 billion (Swiss Re Group, 2012). The Japan earthquake and tsunami of 2011 led to a rapid decline in Toyota's production and resulted in a reduction in profits of $72 million per day (Pettit et al., 2013). More recently, in the wake of the COVID-19 pandemic that started in 2020, 94% of Fortune 1000 firms observed supply-chain disruptions, and 75% of them reported a negative or strongly negative effect on business (Jain, 2021). Araz et al. (2020) considered COVID-19 to be the most severe supply-chain disruption the world has experienced in decades; examples of unexpected challenges have included demand and supply shocks related to hoarding, (foreign) labor shortages, and cross-border transportation restrictions.

The topic of *supply-chain risk management* has attracted many scholars. Several review articles are available, including Ho et al. (2015), which identified the most common steps in SCRM, and Fan & Stevenson (2018), which focused on identifying risk types and proposing risk-mitigation strategies.

1.2. Allocating limited risk-management resources

Strategies to mitigate risks in supply chains often entail significant expenditure in terms of both time and money. First of all, efforts are required to obtain information about risk factors. Manuj & Mentzer (2008) detailed the actions involved in such an endeavor. In particular, they stated that selection of the appropriate parties (i.e., experts) is critical for obtaining meaningful data on the range of possible incidents. Managers from various manufacturing companies and industries, as well as those who worked with a single organization over an extended period of time (thus witnessing the company move through several transformations), should be involved.

Yet, even if it were possible to identify the full set of risks, budget constraints would make it infeasible to eliminate them all (e.g., through cooperation between supply-chain members) or to mitigate them all (e.g., by preparing reserves or building flexibility). For instance, Sherwin et al. (2020) developed risk-mitigation models to deal with at-risk suppliers within the nuclear power plant construction supply chain. Due to the impracticality of managing all risks, the models proposed by these authors allow decision-makers to derive mitigation strategies that meet the firm's budgetary constraints. In a study with similar goals, Khosravi-Farmad & Ghaemi-Bafghi (2020) proposed an integrated network security risk-management strategy based on the Bayesian decision network (BDN). The advantage of the BDN is that it allows network security administrators to realize optimal security countermeasures under budget limitations. El Baz & Ruel (2021) studied the potential role of supply-chain risk management in mitigating the effects of disruptions to the supply chain caused by the COVID-19 pandemic. The authors stated that to improve supply-chain robustness and resilience, firms need to develop interconnected SCRM practices. However, they acknowledged that due to the impact of the pandemic on firms' financial health, some companies might not have the necessary resources and abilities to adopt such practices. Zhang & Guan (2021) proposed a two-stage model to allocate a limited budget among risk response strategies in the context of project management.

As illustrated by the above studies, players in supply chains are generally faced with a greater number of risk factors than they are able to address given the available resources. This implies that a framework needs to be developed to ensure that resources are allocated to risk-mitigation strategies in an appropriate manner.

1.3. Problem definition and contribution

Large-scale systems, such as supply chains, are capital intensive and entail enormous amounts of information. Such information may consist of all future events over an infinite horizon. At any given moment, these events are not fully known; however, data pertaining to these events may be required in order to control the system optimally. Yet, the resources available to managers, in terms of time, personnel, information, and capital, tend to be limited. Moreover, many companies face difficulties handling the vast amounts of complex data that tend to characterize modern working environments (see, for example, the works of Alharthi et al., 2017 and Moktadir et al., 2019 among many others). The present study focuses on the acquisition of information pertaining to future sources of risk. According to Sharma et al. (2022), there is insufficient literature on the topic of risk quantification.

This study develops a new method to overcome the difficulties associated with risk management under constrained resources, and it illustrates the applicability of the method to two real-life supply chains. Thus, the scope of the work is mainly restricted to risk management under two specific settings: a pharmaceutical supply chain and a generalized green supply chain. The underlying principle of our approach is that, in order to achieve effective risk management, decision-makers do not require information about all risks in advance (where information refers to the probability of occurrence and the severity), but only about a limited number of them. As a result, limited resources can be channeled in specific directions when the firm is seeking information about the entire pool of risks. The algorithm at the heart of the approach is a stopping rule based on the concept of entropy. Entropy is a scientific concept, as well as a measurable physical property, that is most commonly associated with a state of disorder, randomness, or uncertainty. Claude Shannon referred to this "missing information" as entropy, in an analogous manner to the use of this term in statistical mechanics, and in so doing, gave birth to the field of information theory. Shannon's definition of entropy has now been universally accepted. The stopping rule proposed in this study seeks to determine, through optimization, the set of risk factors for which information should be revealed. More specifically, the proposed algorithm minimizes the total costs associated with obtaining detailed information about risk factors, while simultaneously minimizing the ineffective utilization ("entropy" in our terms) of available resources, noting that this entropy decreases with the number of risk factors for which accurate information is obtained.

The key research questions addressed in this study are as follows:

(1) How can a management team efficiently select a set of risk factors to address (given that it may not be cost effective or even feasible to address all risk factors)?

(2) How can a simple procedure (i.e., the proposed stopping rule) be applied to a pharmaceutical supply chain and what are the managerial implications?

(3) How can a simple procedure (i.e., the proposed stopping rule) be applied to a generalized green supply chain and what are the managerial implications?

The contributions of this study to the existing literature are as follows:

(a) The suggested model is unique in its approach of balancing two considerations: The first, captured by entropy, measures the resources wasted in the case of inaccurate information about the probabilities of occurrence and impacts of risk factors. The second is the cost associated with the efforts expended in collecting accurate information about risk factors.

(b) We provide a numerical illustration of the proposed model for the case of a pharmaceutical supply chain. This application was chosen because, unlike many other supply chains, the pharmaceutical SC is characterized by very high complexity due to factors such as unpredictable demand volatility, the immense scope of the delivered items, and the short lifecycles of the products. Accordingly, the supply chain is exposed to a wide range of risks, a full investigation of which would require considerable time and resources.

(c) We provide a numerical illustration of the model for the case of a generalized green supply chain. This application was chosen due to the increasing global interest in environmental issues, along with the fact that, since this is a relatively new field, the operation of green supply chains entails new threats that have not been widely discussed.

(d) The proposed model is realistic in terms of its two key assumptions, namely that full, accurate information is not available and that risk-management resources are limited.

2. Literature review

This study focuses on the applicability of a simple stopping rule for the purpose of managing risks in two supply chains. Accordingly, the theoretical aspects of the model and its mathematical analysis are not presented in this paper. Similarly, the literature review presented below, rather than focusing on theoretical work, highlights studies in which risk-management models were applied to real-world systems - in particular, to supply chains. The review focuses on three main areas: (1) acquiring information about risk factors; (2) managing risks under limited information; and (3) risk-management case studies.

2.1. Acquiring information about risk factors

To assess vulnerabilities in a supply-chain context, companies must identify direct risks to their operations, and risks to all other entities, including those caused by the linkages between organizations (CIPS, 2013). Identifying risks and assessing their likelihood and potential impact on operations is a complex and challenging task for a single organization (Jüttner, 2005). According to Norrman & Jansson (2004), risk mapping, i.e., a structured approach for mapping risk sources and understanding their potential consequences, is one of the essential tools. Two commonly used techniques for risk mapping are “fault tree analysis” (FTA) and “event tree analysis” (ETA).

Nakandala et al. (2017) used a hierarchical holographic model (HHM) to allow managers to identify potential risk scenarios within the fresh-food supply chain. Following risk identification, the authors conducted a risk assessment procedure based on a hybrid method incorporating qualitative and quantitative approaches. Prakash et al. (2017) held discussion and brainstorming sessions to reveal experts' opinions on risk factors in the dairy industry. The risks were then quantified by means of an interpretive structural modeling (ISM) approach, which aims to identify and summarize relationships among the specific variables that define a problem. Lawrence et al. (2020) suggested identifying risk factors through an extensive search of the public literature domain. Then, in order to construct a risk quantification model with a high degree of confidence, multiple sources were used to gather details of the events that unfolded after the disaster. Information was extracted from news articles, videos, government reports and other sources, and these data were used to construct probability tables. In recent work, Zhu & Liu (2023) constructed a three-layer back propagation neural network for risk prediction within the prefabricated building supply chain.

The traditional approach to risk assessment involves placing risks in a prioritized order based on their likelihood and severity (El Baz & Ruel, 2021). Information about likelihood and severity may be gathered from a variety of sources, including historical data, expert opinion, and scenario thinking. In contrast to this approach, the current study does not assume that information is known for all risk factors.

2.2. Managing risks under limited information

An increasingly common practice when conducting risk assessment of a large-scale system is to consider only partial information. This may be because of a lack of full, accurate information. Duong et al. (2019), for instance, stated that one of the main barriers to effective management of agricultural risks lies in the very limited information about the risks themselves. The COVID-19 pandemic is a recent reminder of how situations may arise where people are forced to perceive risks based on partial and rapidly changing information (Pine et al., 2021).

However, other scholars have argued that complete information may not be necessary. The suggestion that it is possible to obtain efficient solutions under limited (i.e., partial or imperfect) information is not new, and has been utilized in numerous fields – both in theoretical work and in practice. Menzies & Sinsel (2000) proposed a decision tree combined with a pruning method for practical, large-scale what-if queries in relation to a software-effort estimation project. They characterized the space of what-ifs by searching for significant ranges, i.e., small sets of parameter values that are most influential in terms of achieving some desired result. Herbon et al. (2003) developed a pseudo-stochastic model for the optimal control of a dynamic system over a given planning horizon. They investigated the impact of uncertain future events on decision-making in a stochastic environment and demonstrated that one can use a substantially reduced amount of information to achieve near-optimal control of a real dynamic system. Cao et al. (2014) proposed a partial-information state-based approach to optimize the long-run average performance in a partially observed Markov decision process (POMDP).

Models that assume partial information have also been employed in the field of risk management. Kraev & Tikhonov (2019), who considered human resource management, focused on the personnel screening stage, when very little information about the applicant is known. Thus, there is a high risk of recruiting an inappropriate candidate. To overcome this obstacle, the authors proposed using data from social networks where the applicant is a member. Rios et al. (2020) used attack-defense trees to estimate system risks in the context of assaults on Internet of Things (IoT)-based smart grid systems. In such a system, there is usually limited or no information about the attack events. Zweifel (2021) used linear partial information theory to deal with imprecise information in the insurance domain where the risk profile of a newly enrolled customer is not fully known.

2.3. Case studies of risk factors in supply chains

This subsection describes case studies focusing on managing risk factors within various types of supply chain, including, but not limited to, pharmaceutical and green supply chains.

2.3.1. Pharmaceutical supply chains

Wang & Jie (2020) proposed a framework for managing uncertainty and risk in pharmaceutical supply nets. In particular, the authors determined that the threats can be divided into two main categories: internal and external. To mitigate these risks, the authors investigated how the risks were affected by various supply-chain integration capabilities, such as supply-chain visibility, agility, and flexibility. Lawrence et al. (2020) proposed a static Bayesian network model to quantify the impact of severe weather on pharmaceutical supply-chain performance, with a view to facilitating the development of effective risk control and mitigation strategies. Sharma et al. (2022) considered the case of the Indian pharmaceutical industry and assessed the impacts of the risks using a fuzzy synthetic evaluation (FSE) method, which is an appropriate technique when dealing with multiple parameters having different risk levels. Bø et al. (2023) investigated how the COVID-19 crisis has affected the risk, resilience, and reliability of Norwegian food and pharmaceutical supply chains – industries that had to maintain the supply of essential goods despite societal lockdown.

2.3.2. Green supply chains

Giannakis & Papadopoulos (2016) explored risks within sustainability-related supply chains with a view to gaining knowledge about how to manage these risks more effectively. The risks were detected through a brief interview with supply-chain managers from 30 companies representing different industries in the UK and France. Risk analysis and assessment was carried out by means of the failure modes and effects analysis (FMEA) approach. Unlike Giannakis & Papadopoulos (2016), Mangla et al. (2018) focused on a specific plastic manufacturing firm operating in North India. Being the leading producer of plastic-based products on the domestic and global market, the firm seeks to maximize its economic-ecological gains, and thus, it is committed to adopting green supply-chain (GSC) initiatives in various aspects of its business. By using fuzzy FMEA analysis to assess the risks, the authors found that the main barriers to implementing GSC initiatives are inaccuracy in using green methodology (i.e., processes, operations, machines, and equipment) and mismanagement in the reverse logistics network design. Similarly to Mangla et al. (2018), in the current work, we derive the main risk factors through a thorough literature review.

India’s pharmaceutical sector has shown considerable growth over the last decade. Despite the advantages of such growth, a negative consequence has been the substantial increase in medical waste (such as expired medications and contaminated products), which places a burden on the environment and can be detrimental to public health. To address this problem, Kumar et al. (2019) investigated how to integrate green supply-chain concepts into India's pharmaceutical sector. A consequential two-step approach was proposed. In the first step, the main green-related risks within the pharmaceutical industry were revealed based on a literature review coupled with the fuzzy Delphi approach. In the second step, these risks were prioritized using a fuzzy analytical hierarchy process. Similarly to Kumar et al. (2019), Shakeri et al. (2020) identified the main risk factors that hinder GSC activities within the pharmaceutical industry in Iran, with an emphasis on the medicine supply chain of the Imam Reza Hospital of Mashhad. With the help of a literature review and expert opinions, 31 significant risks were detected. Unlike previous studies, where the risks were investigated in isolation, the authors suggested exploring the interrelations between risks and their influence on the performance of the supply chain. The Bayesian belief networks (BBN) approach was used to prioritize and analyze the risks. The results revealed that the main risk factors affecting the successful implementation of GSC activities are an inefficient logistics network design, supplier quality issues, and green raw material supply disruption.

According to Chen et al. (2022), most of the research devoted to managing risks within green supply chains has focused on detecting and assessing the threats related to particular phases within green operations, e.g., refurbishing or remanufacturing. To adequately address all risks, the entire green process, starting from material purchase and ending with the recycling or disposal of goods, needs to be considered. Focusing on the case study of a Taiwanese laptop manufacturer, Chen et al. (2022) first identified the main green-related risk factors through an extensive literature survey and discussion with a panel of experts. Then, based on the FMEA procedure, the risk priority number (RPN) of each risk was calculated. However, unlike previous studies where the RPN is a simple product of the risk's severity, occurrence and detection, Chen et al. (2022) separated each of these categories into different dimensions, so-called RPN subcomponents. For instance, they assumed that the severity of a risk is related to four properties referred to as quality, time, elasticity, and cost. Next, they calculated the relative weights of the RPN subcomponents for each green risk factor using the analytic network process (ANP) method, and finally, they ranked the risks based on a combination of grey relational analysis and the previously determined ANP weights. Medina-Serrano et al. (2021) presented a case study of a leading manufacturer of electrical products in Germany aiming to improve the company's sustainability through effective risk management procedures. In Gao et al. (2022), the authors identified the main risk factors that may impede the implementation of green supply-chain management practices within small and medium enterprises (SMEs) in China. To identify the causal relationships among the risk factors, they developed and implemented a hybrid decision-making tool based on a combination of fuzzy logic and the DEMATEL approach. The research identified 17 risk factors and determined that the most effective risk-mitigation strategies would be supplier collaboration, support from company management, and support from external authorities.

2.3.3. Other sectors

Diabat et al. (2012) developed and implemented a decision tool to analyze and mitigate risks within RMK, a leading producer of food products in South India. The authors classified risks according to their criticality based on cross-impact matrix multiplication (MICMAC) analysis, identifying four risk groups: autonomous, dependent, linkage, and driver/independent. The authors concluded that risks in the "autonomous" group require the closest attention of decision-makers, and consequently, they devised mitigation strategies to deal with such risks. Globalization has created the opportunity for many countries to procure products from a wide range of importers, including food importers. To avoid a situation in which the consumption of imported products may be harmful to health, an effective multi-criteria risk prevention tool is needed to rank the suppliers. Puertas et al. (2020) developed such a tool for the case of the importation of cereals to the European Union. The tool is based on well-known techniques such as TOPSIS, ELECTRE, and cross efficiency (CE). The authors identified corruption, environmental sustainability in agriculture in the country of the supplier, and logistics issues as risk factors for importing poor-quality products. Hendayani et al. (2021) conducted interviews among the managers of the firm KPBS Pangalengan (a dairy company in Bandung, Indonesia) to collect information regarding the risks within its supply chains. To identify ways of mitigating these risks, the authors developed a procedure based on a combination of failure mode and effect analysis and quality function deployment (QFD). This resulted in the identification of seven risk-mitigation strategies for the company. For more papers in this field, we refer the reader to the recent extensive review of risk management in food supply chains by Azizsafaei et al. (2021).

Oke & Gopalakrishnan, (2009) investigated the connection between the type of risk and the appropriate mitigation strategy within North America's retailer supply chain. They found that mitigation policies may either be specific (i.e., designed to cope with a particular kind of risk) or generic (i.e., capable of dealing with any risk). In particular, specific mitigation policies are more appropriate for low-likelihood and high-impact risks, whereas generic mitigation strategies are suited to high-likelihood and low-impact risks. To manage risks in an automotive supply chain, with an emphasis on the product life cycle (PLC) and the operational process cycle (OPC), Salehi Heidari et al. (2018) implemented an integrated fuzzy AHP and fuzzy TOPSIS approach. The proposed model allows the ranking of various risk-management practices (including admission, weakening, transfer, and avoidance) to reduce the risk factors within the supply chain. The effectiveness of the proposed method was tested on a real-life manufacturing company in the automotive industry of Iran. Jonathan et al. (2020) aimed to formulate recommendations for the effective risk management of the supply chain of Eskom – South Africa's primary electricity supplier. The first stage involved constructing a focus group comprising 22 company managers. The managers were interviewed and their responses were analyzed to derive recommendations for risk management. A key recommendation was the need to continuously monitor external and internal customer services.

Similarly to the approach used in the current work, Dohale et al. (2023) retrieved the principal risk factors and their characteristics (i.e., severity and probability of occurrence) from multiple case studies within the apparel industry in India during the COVID-19 pandemic. They also used these case studies to derive a set of possible mitigation strategies. The data were verified by a group of experts, and appropriate mitigation strategies were selected by implementing a risk mitigation strategy matrix. The authors determined that the most critical risks were demand uncertainty and supply disruption, and that these risks may be alleviated by incorporating flexibility and postponement strategies. Flexibility refers to the ability to deploy an organization's resources efficiently in order to respond to unexpected change, whereas postponement involves delaying (or slowing down) the production and distribution of goods as long as exact information about demand is not available.

Sabila et al. (2022) focused on risk management within the agricultural supply chain in Indonesia. To identify the risks, the authors reviewed previous literature and gathered expert opinions. The risks were then prioritized using the fuzzy FMEA method, and finally, appropriate mitigation strategies were determined via the TOPSIS approach.

In the era of advanced technologies based on web interconnectivity, blockchains are vital for ensuring user anonymity and immutability. Such technology has already been applied to numerous spheres of daily life, ranging from healthcare to the educational sector and secret military services. Dua et al. (2023) explored the role of blockchain technology in mitigating the customer's perceived risks (e.g., financial, psychological, social, performance, and physical) within different supply chains. In particular, the authors considered the cases of precious metal manufacturing, fast-moving consumer goods (FMCG), the automotive industry, and pharmaceutical nets. Based on fuzzy analytical hierarchical processing (F-AHP), the authors detected critical risks across these supply chains and offered appropriate mitigation tactics.

Trucking services play a vital role in the day-to-day operation of numerous production and service companies. This industry faces multiple threats that may disrupt its operations. Therefore, selecting appropriate risk-mitigation strategies is critical. To cope with this problem, Dadsena et al. (2019) developed an integrated multi-objective optimization model compromising three objective functions given limited budget: feasibility of mitigation strategies, cost reduction, and targeted level of risk. In Qazi et al. (2018), the authors devised a method to prioritize risks, discover the interrelations between them, and explore suitable mitigation strategies. They used Bayesian belief networks and fault tree analysis (FTA) to create a network of risks, allowing them to understand their interconnectivity. They then assessed the risks based on BBNs and expected utility theory (EUT). Finally, to choose an appropriate strategy to mitigate a given risk, the authors employed the "swing weights" approach. The primary purpose of this method is to achieve a trade-off between the efficiency of the proposed mitigation strategy and its costliness. Such an approach allows decision-makers to select only those mitigation strategies that are feasible given the budget constraints. The process was demonstrated through a case study conducted in a global manufacturing supply chain involving semi-structured interviews and focus-group sessions with experts in risk management.

2.4. Gap relative to the existing literature

Table 1 summarizes the previous work most relevant to the problem considered in this paper, and classifies the studies according to key characteristics. From this table, it can be seen that risk management generally starts with risk identification. During this procedure, the decision-makers aim to (a) uncover all relevant risks and (b) acquire accurate information about their probability of occurrence and corresponding severity. Usually, this information is obtained by conducting interviews with internal managers and external specialists. Despite having significant advantages, this method is both time- and resource-intensive – a factor that has not been taken into account in most previous studies (see column entitled "Constraint type" in Table 1). Given that a firm's available resources for risk identification tend to be limited, the acquired data will be incomplete and imprecise. Consequently, the firm's risk management plan will suffer as a result of the information gap, which in turn may lead to resource waste.

Table 1. A comparison of the proposed model with related work

Paper	Bø et al. (2023)	Sharma et al. (2022)	Lawrence et al. (2020)	Puertas et al. (2020)
Application sector(s)	Norwegian food and pharma supply chains	Indian pharma industry	U.S. pharma supply chain	European Union food chain
Model classification	Impact on risk, resilience and reliability	Fuzzy synthetic evaluation	Bayesian network approach	Discrete decision methods
Information needed about risk factors	Likelihood and severity	Likelihood	Likelihood	Weight and scaled value of each risk-related factor
Constraint type	None	None	None	None
Solution method	Several rounds of semi-structured interviews	Determining most contributive risks with four risk parameters	Predictive inference reasoning	Combination of TOPSIS, ELECTRA and CE methods
Additional characteristics	Proposes frequent assessment of identified risks, followed by risk	Identifies the critical risks that need to be mitigated	Identifies severe weather as an important risk when selecting suppliers	Ranks the suppliers with respect to the identified risk factors

Paper	Salehi Heidari et al. (2018)	Dua et al. (2023)	Dohale et al. (2023)	Mangla et al. (2018)
Application sector(s)	Automotive manufacturing company in Iran	Metal manufacturing, fast-moving consumer goods, automotive and pharmaceutical	Apparel industry in India	Green plastic supply chain in India
Model classification	Fuzzy discrete decision methods	Fuzzy discrete decision methods	Quantitative risk assessment methodology	Fuzzy risk assessment tool

Information needed about risk factors	Organizational performance factors and risk operational practices	Relative importance of each risk factor	Likelihood and severity	Probability of occurrence, severity and non-detection
Constraint type	None	None	None	None
Solution method	Combination of fuzzy AHP and TOPSIS methods	Fuzzy AHP	Risk assessment matrix	Fuzzy FMEA
Additional characteristics	Suggests various practices for decreasing operational risks	Allows assessment of the linkage between (a) the risks and (b) the capabilities and assurance provided by blockchain	Identifies demand uncertainty and supply disruption as the most critical risks	Develops a benchmarking framework that facilitates GSC management and planning

Paper	Kumar et al. (2019)	Chen et al. (2022)	Dadsena et al. (2019)	Qazi et al. (2018)	The suggested stopping rule
Application sector(s)	Green pharma supply chain in India	Green laptop-manufacturer supply chain in Taiwan	Trucking industry in India	Aero, a global manufacturing supply chain	Pharma and generalized green supply chains
Model classification	Fuzzy discrete decision methods	Discrete decision methods and relational analysis	Multi-objective optimization	BBN-based modeling of a risk network combined with expected utility theory	Non-linear, integer optimization problem
Information needed about risk factors	Risk factor evaluation	Expected importance of each risk factor	The current level of risk and the loss incurred due to its occurrence	Conditional probability and cost of mitigation strategies	Likelihood and severity of a subset of the risk factors

Constraint type	None	None	Budget	Budget	Budget
Solution method	Fuzzy Delphi approach and fuzzy AHP	FMEA, ANP, grey relational	Single-objective problem using global criterion method	Fault tree analysis	One-dimensional online search with speed O(N)
Additional characteristics	Offers a benchmark model to manage GSC initiatives and sustainable issues in the pharma industry	Focuses on the entire green process	Examines and identifies the optimal range of budgetary investment	Derives a framework that can model the real-life trade-off between conflicting and interdependent objectives	Results in low utilization of the budget

Based on the comprehensive literature review provided above and the comparison shown in Table 1, the present study makes the following contributions to the existing literature:

(a) We do not require that the likelihood and severity are known for all risk factors; this information only needs to be acquired for some of the risk factors.

(b) Our approach builds an optimization model and considers limited resources and information.

(c) We devise a simple and highly efficient procedure, implemented online, to address risk factors in supply chains under a limited budget. The suggested stopping rule can be implemented very quickly for any problem size, i.e., with complexity O(N).

(d) We illustrate the applicability of the proposed model to two real-life supply chains – a pharmaceutical SC and a generalized green SC. We demonstrate that the proposed model may be successfully implemented to manage risk factors faced by both types of supply chain. Moreover, in the case of the generalized green supply chain, we conduct a comparative analysis between our approach and a widely used technique, and show the superiority of the former.

Section 3 provides a detailed description of the proposed model and its solution algorithm. The implementation of the model within pharmaceutical and environmentally-oriented supply chains is provided in Sections 4 and 5, respectively. Section 6 concludes our study.

3. The model and the stopping rule

3.1. The optimization model

The proposed model is based on the assumption that firms allocate a limited budget to the process of risk management. Thus, to manage the firm's risks effectively, decision-makers need to adopt a logical approach when deciding how to utilize the available assets. A portion of these assets is used to identify the risks and to acquire information about them – specifically, their probability of occurrence and their impact. The quality of the obtained information plays a vital role in deciding which threats should be a priority for mitigation strategies. Consequently, it is necessary to decide which risks warrant the acquisition of complete and accurate information and which may be ignored in the light of the restricted budget and/or the lack of a clear benefit. The model proposed herein aims to tackle this challenging question.

In our model, the number of risks for which precise information will be collected is a decision variable f. Accordingly, the remaining risks $N-f$, wherein N represents the total number of relevant risks under investigation, may be neglected. The greater the value of f, the higher the costs associated with acquiring precise information. This effect, which constitutes one of the terms of our objective function, is modeled through a flexible polynomial function of a pair of given parameters α, β ($\alpha > 0, \infty > \beta > 0$). More specifically, α represents a scaling factor applied to the cost of acquiring accurate information and β is a coefficient that characterizes the specifications of both the supply chain and the management policy regarding obtaining information about risk factors. When $0 < \beta < 1$, the polynomial function becomes concave, reflecting the case where learning has taken place due to experience gained from investigating former risk factors. In the case where $\beta = 1$, the function is linear, implying that the costs of acquiring information are identical for each risk factor. Finally, in the remaining case, where $\beta > 1$, a convex curve reflects a strategy in which risk factors that are more accessible (i.e., cheaper to estimate) are addressed first. The objective, $Z(f)$, defined in equation (1) below, represents the monetary penalties incurred when addressing only a limited number of risk factors. The first term in (1) reflects the fact that incomplete information can lead to the ineffective utilization (entropy in our terms) of available resources. This entropy decreases with the number of risk factors for which accurate information is obtained, thereby reducing the amount of incorrect and incomplete information, reduces the ineffective utilization of resources (i.e., the entropy). The second term in the objective function represents the costs of acquiring precise information. The cost increases with the number of risk factors for which accurate information is obtained. Some of the information about risk factors is unknown, thus, the entropy measures the dispersion of the density function of the likelihoods of the risk factors given the unknown information is modeled by a uniform density. Mavi et al. (2016) used Shannon entropy to weigh criteria in the context of supplier selection. Khorram (2020) developed a novel approach for managing risks pertaining to port container terminals. The Shannon entropy concept was used to convert the subjective weights (proposed by experts) to objective weights, while the fuzzy VIKOR technique was implemented to rank and prioritize the failure modes on the basis of maximum "group utility" and minimum "individual regret."

Based on the above discussion, the unconstrained optimization problem is characterized by the following objective function:

$$\min_{0 \le INT\ f \le N} Z(f) = \left\{ \left(\frac{H(f)}{\ln(N)} \right) + \alpha \left(f \middle/ N \right)^{\beta} \right\}, \tag{1}$$

where $H(f)$ denotes the entropy of N investigated risks, and complete and accurate information is known for f of these risks. The entropy is defined by

$H(f) = -\left[\sum_{i=1}^{f} r_i \ln(r_i) + \sum_{i=f+1}^{N} \left(\frac{1-\sum_{i=1}^{f} r_i}{N-f} \right) \ln\left(\frac{1-\sum_{i=1}^{f} r_i}{N-f} \right) \right]$, where r_i is the normalized impact of risk i. By definition, $H(0) = \ln(N)$ and $\sum_{i=1}^{N} r_i = 1$.

To determine the decision variable f such that objective function (1) is minimized, we develop a stopping-rule algorithm presented in the following subsection. To simplify the development of this algorithm, we analyze problem (1) under the assumption of a continuous setting rather than a discrete one. Such a presentation enables us to utilize certain mathematical properties (e.g., convexity or concavity) of $H(f)$.

Assumptions:

1. The management team can suffer the consequences of addressing only a subset of the risk factors.

2. Complete and accurate information may only be available for some of the risk factors.

3. The stopping rule performs sufficiently well to replace the optimal solution (which is unknown).

4. The likelihoods and impacts (i.e., potential damage) of the risk factors are the only factors needed to prioritize them.

3.2. The stopping rule

Starting from objective (1), we can state without proof that $\left.\frac{\partial H(f)}{\partial f}\right|_{f=0} = -\frac{1}{N}$, i.e., that the first component initially decreases with an increase in the number of known risk factors. On the other hand, the second component, $\alpha\left(f/N \right)^{\beta}$, starts at 0 and increases with *f*. These statements are not sufficient to postulate that the objective is convex. Indeed, the shape of the function depends on the sequence in which the risk factors are addressed, and it has been demonstrated in real-world applications that non convex curves may arise. We apply an axiomatic stopping rule that simplifies the procedure. According to this rule, the decision-maker seeks accurate information about the next risk (its probability of occurrence and its impact) provided the objective further decreases. An alternative strategy would be to set $f = N$, meaning that the decision-maker acquires accurate information about all risk factors. Applying such a strategy would of course allow the decision-maker to determine (retrospectively) the optimal number of risk factors. However, it is likely that the optimal number of risk factors, f^*, is significantly smaller than *N*. Therefore, a decision-maker operating under such a strategy would not be able to reap the benefits (i.e., a smaller objective) since the resources required to obtain full information would already have been wasted.

The following subsection provides a numerical illustration of the initial procedures that are required before applying the proposed model to any application. It is assumed that similar procedures have already been carried out for the two applications presented in Sections 4 and 5; therefore, in these case studies, only the optimization stage is illustrated.

3.3. Preparing the initial vector of normalized impacts

The initial vector of normalized impacts, which consists of the products of the probabilities and the impacts, is sufficient information to apply the stopping rule. Assuming that there are $N = 20$ risk factors (identical to the number of risk factors in both of the applications studied below), we provide an example of a table showing the information pertaining to these risks (see Table 2). The table is divided into four sections corresponding to the following four sets: $\{O\},\{A\},\{B\},\{C\}$. Set $\{A\}$ includes risk factors for which only information about the probability of occurrence in a given planning horizon is known. Set $\{B\}$ consists of risk factors for which only information about the impact of the risk (should it be realized) is known. Set $\{C\}$ includes risk factors for which neither the probability nor the impact is known. Finally, set $\{O\}$ includes risk factors for which complete information is available.

Table 2. Illustrative example of a set of sorted risk factors, along with their likelihoods and expected impacts. The impact is measured in terms of the cost of the damage in New Israeli Shekels (NIS)

Risk factor	Set	Probability of occurrence (per unit time)	Impact (10^6 NIS)
Risk factor 1	$\{O\}$	0.1	2
Risk factor 2	$\{O\}$	0.05	1
Risk factor 3	$\{O\}$	0.2	4
Risk factor 4	$\{O\}$	0.7	10
Risk factor 5	$\{O\}$	0.01	20
Risk factor	Set	Probability of occurrence (per unit time)	Impact (10^6 NIS)
Risk factor 6	$\{A\}$	0.3	Unknown
Risk factor 7	$\{A\}$	0.01	Unknown
Risk factor 8	$\{A\}$	0.1	Unknown
Risk factor 9	$\{A\}$	0.27	Unknown
Risk factor 10	$\{A\}$	0.2	Unknown
Risk factor	Set	Probability of occurrence (per unit time)	Impact (10^6 NIS)
Risk factor 11	$\{B\}$	Unknown	0.5
Risk factor 12	$\{B\}$	Unknown	20
Risk factor 13	$\{B\}$	Unknown	2
Risk factor 14	$\{B\}$	Unknown	10
Risk factor 15	$\{B\}$	Unknown	100

Risk factor	Set	Probability of occurrence (per unit time)	Impact (10^6 NIS)
Risk factor 16	$\{C\}$	Unknown	Unknown
Risk factor 17	$\{C\}$	Unknown	Unknown
Risk factor 18	$\{C\}$	Unknown	Unknown
Risk factor 19	$\{C\}$	Unknown	Unknown
Risk factor 20	$\{C\}$	Unknown	Unknown

Defining the first J_O ($J_O \le N$) risk factors to be the risk factors in set {O}, we determine the average probability and impact values over the "more informed" sets and then we assign these values to the "less informed" sets; that is,

$$\hat{p}_i = \frac{\sum_{i=1}^{J_O} p_i^O + \sum_{i\in\{A\}} p_i^A}{|O|+|A|} = 0.194 \ , \qquad i \in \{\{B\},\{C\}\} \tag{2}$$

where p_i denotes the realization probability (known or unknown) of risk factor *i* over a given horizon, and

$$\hat{d}_i = \frac{\sum_{i=1}^{J_O} d_i^O + \sum_{i\in\{A\}} d_i^B}{|O|+|B|} = 16.95 \ , \ i \in \{\{A\},\{C\}\} \ . \tag{3}$$

where d_i denotes the expected potential damage (known or unknown) of risk factor *i* over a given horizon. We denote the normalized impact of risk factor i in sets $\{O\}$, $\{A\}$, $\{B\}$, and $\{C\}$ by r_i^O, r_i^A, r_i^B and r_i^C, respectively:

$$r_i^O = \frac{p_i^O d_i^O}{S} \ i \in \{O\} \qquad ; \qquad r_i^A = \frac{p_i^A \hat{d}_i}{S} \ i \in \{A\} \ ; \qquad r_i^B = \frac{\hat{p}_i d_i^B}{S}, \qquad i \in \{B\} \ ;$$

$$r_i^C = \frac{\hat{p}_i \hat{d}_i}{S}, \ i \in \{C\}, \ \text{where} \sum_{i=1}^{N} r_i = 1 \ \text{and}$$

$$S \equiv \sum_{i=1}^{J_O} p_i^O d_i^O + \sum_{i\in\{A\}} p_i^A \hat{d}_i + \sum_{i\in\{B\}} \hat{p}_i d_i^B + \sum_{i\in\{C\}} \hat{p}_i \hat{d}_i = 8.25 + 14.916 + 25.705 + 16.4415 = 65.3125$$

Table 3 shows the result of implementing the above procedures.

Table 3. Sorted risk factors, along with their likelihoods and potential impacts, after assigning averaged values to missing data

Risk factor	Probability of occurrence (per unit time)	Impact (10^6 NIS)	Normalized impact
Risk factor 1	0.1	2	0.0030622
Risk factor 2	0.05	1	0.0007655
Risk factor 3	0.2	4	0.0122488
Risk factor 4	0.7	10	0.1071770
Risk factor 5	0.01	20	0.0030622
Risk factor	Probability of occurrence (per unit time)	Impact (10^6 NIS)	Normalized impact
Risk factor 6	0.3	16.95	0.0778564
Risk factor 7	0.01	16.95	0.0025952
Risk factor 8	0.1	16.95	0.0259521
Risk factor 9	0.27	16.95	0.0700708
Risk factor 10	0.2	16.95	0.0519043
Risk factor	Probability of occurrence (per unit time)	Impact (10^6 NIS)	Normalized impact
Risk factor 11	0.194	0.5	0.0014852
Risk factor 12	0.194	20	0.0594067
Risk factor 13	0.194	2	0.0059407
Risk factor 14	0.194	10	0.0297033
Risk factor 15	0.194	100	0.2970335
Risk factor	Probability of occurrence (per unit time)	Impact (10^6 NIS)	Normalized impact
Risk factor 16	0.194	16.95	0.0503472
Risk factor 17	0.194	16.95	0.0503472
Risk factor 18	0.194	16.95	0.0503472
Risk factor 19	0.194	16.95	0.0503472
Risk factor 20	0.194	16.95	0.0503472

In the next two sections, we demonstrate the effectiveness of the proposed stopping-rule algorithm (which, as mentioned, only requires the vector of normalized impacts as an input) by implementing it on two real-life case studies: a pharmaceutical supply chain and a generalized green supply chain. Based on data gathered from the operation of the supply chains, the approach is tested for multiple computerized scenarios wherein the scaling coefficient α and the learning coefficient β are varied. The results are summarized and analyzed to derive managerial insights and suggestions.

4. Application in a pharmaceutical supply chain: method and results

4.1. Pharmaceutical supply chains

Pharmaceutical supply chains deliver various medical supplies (e.g., drugs) from production facilities to wholesalers or directly to pharmacies, clinics, and hospitals. According to recent reports (see, for example, Grand View Research, 2020), the global pharmaceutical logistics market was valued at USD 69.0 billion in 2019 and is expected to increase. The growing competitive pressure associated with the globalization of markets, coupled with the rising complexity of deliveries, short product lifecycle, and volatility of demand, renders pharmaceutical supply chains extremely vulnerable to diverse risks.

The COVID-19 pandemic has further highlighted the need for agile and robust pharmaceutical supply chains, since, unlike many other logistics chains, any risk to the operation of the pharmaceutical chain may have a direct effect on end-user health and mortality, rather than merely wasting resources. Thus, detecting and mitigating the risk factors within pharmaceutical chains is of critical importance.

We begin by identifying and characterizing the risks, i.e., determining the probability of occurrence within a given unit of time and the corresponding impact. A common method of obtaining this information is to conduct a questionnaire among decision-makers in the field (see, for instance, the works of Breen, 2008; Ouabouch & Amri, 2013; and Jaberidoost et al., 2015). Due to the distinct geographical, social, and political aspects of a given pharmaceutical supply chain, the risks vary from one study to another; yet, numerous risk factors appear to be common to many or all supply chains. Based on an analysis of the relevant literature (see, for example, Ouabouch & Amri, 2013 and Agorzie et al. 2017), we identified 20 such common risk factors, which are presented in Column #1 of Table 4. The practice of identifying the common risk factors through a literature survey is well known and has been used in various studies. For example, Aloini et al. (2012) reviewed the literature pertaining to construction supply chains and identified 13 common risk factors. Ren et al. (2022) consulted literature on cold chain disruptions to identify risk factors that may potentially cause packaging failure. In this study, to validate the data retrieved from the literature, we also talked with experts in the field. In particular, experts from the CLALIT Healthcare Maintenance Organization (HMO), the second-largest HMO in the world, were involved A similar approach for identifying, appraising, and validating the risk factors was adopted in the case of environmentally-oriented supply chains (see Section 5).

Information regarding the probability of occurrence and the impact of each risk (see Columns #2 and #3 respectively in Table 4) is presented on a numeric scale ranging from 1 to 5, where a rating of one means either a low probability of occurrence or a minor impact, while a rating of five has the opposite meaning. The greater the likelihood and the impact (i.e., potential damage) of a given risk factor, the higher its expected impact. Thus, we calculated the expected impact of each risk (Column #4) by multiplying Column #2 by Column #3. The data in Table 4 allow us to proceed to the next stage wherein the stopping-rule algorithm is implemented.

Table 4. Risk factors in pharmaceutical chains and their scaled characteristics (probability of occurrence and impact)

Risk number	Risk factor f (#1)	Retrieved data (in numeric scaled form ranging from 1 to 5)		Expected impact (#4)
		Probability of occurrence (#2)	Impact (#3)	
1	Untimely delivery of products to customers	2.4920	4.1740	10.40161
2	Inefficiency in transport infrastructure	2.2280	3.9915	8.89306
3	Compliance problems (e.g., return of inadequate drugs)	2.6360	3.0000	7.90800
4	Failure of operational equipment at company's warehouse	2.0600	3.0000	6.18000
5	Significant decline in market prices	2.4300	3.7695	9.15989
6	Outage of IT system	2.4480	3.3630	8.23262
7	Delivery chain disruptions (pandemics, cyber-attacks, natural disasters)	2.1800	3.6000	7.84800
8	Accidental product damage during loading, unloading, or holding procedures	2.5080	3.0190	7.57165
9	Supplier quality problems	2.5630	4.3955	11.26567
10	Unpredictable regulatory trade barrier	2.3500	3.5300	8.29550
11	Poor stock visibility	2.9080	3.0840	8.96827
12	Unexpected demand fluctuations	2.6870	3.8100	10.23747
13	Theft in the stores and the delivery sectors	3.2200	3.6600	11.78520
14	Supplier delivery failure (incapable supplier)	2.6240	3.3420	8.76941
15	Untimely delivery of products by suppliers	3.1840	3.2580	10.37347
16	Inventory shortage	3.0370	3.6765	11.16553
17	Product expiration along the supply chain	3.3040	4.0240	13.29530
18	Excess stocking	3.3320	2.9830	9.93936
19	Significant increase in wholesale prices	3.0000	3.7300	11.19000
20	Lack of personnel within inbound and outbound logistics	2.9560	4.1430	12.24671

The next step was to use the expected impact values, shown in Column #4 of Table 4, to calculate the normalized impact of each risk, r_i (see Table 5). Recall that the sum of all normalized impacts is 1.

Table 5. Risk factors in a pharmaceutical supply chain and their normalized impacts under full information (e.g., historical data)

Risk number	f	Normalized impact r_i	Risk number	f	Normalized impact r_i
1	Untimely delivery of products to customers	0.05369	11	Poor stock visibility	0.04629
2	Inefficiency in transport infrastructure	0.04591	12	Unexpected demand fluctuations	0.05284
3	Compliance problems (e.g., return of inadequate drugs)	0.04082	13	Theft in the stores and the delivery sectors	0.06083
4	Failure of operational equipment at company's warehouse	0.03190	14	Supplier delivery failure (incapable supplier)	0.04527
5	Significant decline in market prices	0.04728	15	Untimely delivery of products by suppliers	0.05355
6	Outage of IT system	0.04250	16	Inventory shortage	0.05764
7	Delivery chain disruptions (pandemics, cyber-attacks, natural disasters)	0.04051	17	Product expiration along the supply chain	0.06863
8	Accidental product damage during loading, unloading, or holding procedures	0.03908	18	Excess stocking	0.05131
9	Supplier quality problems	0.05815	19	Significant increase in wholesale prices	0.05776

Risk number	f	Normalized impact r_i	Risk number	f	Normalized impact r_i
10	Unpredictable regulatory trade barrier	0.04282	20	Lack of personnel within inbound and outbound logistics	0.06322

Now, based on the data in Table 5, we use (1) to compute the value of the corresponding objective function, $Z(f)$, where the entropy, $H(f)$, is computed according to $H(f) = -\left[\sum_{i=1}^{f} r_i \ln(r_i) + \sum_{i=f+1}^{N}\left(\frac{1-\sum_{i=1}^{f} r_i}{N-f}\right)\ln\left(\frac{1-\sum_{i=1}^{f} r_i}{N-f}\right)\right]$. By definition, $\sum_{i=1}^{N} r_i = 1$ and $H(0) = \ln(N)$. The calculation of the objective function also requires the values of α and β to be known. Recall that parameter α is a scaling factor. Its exact estimation is by no means trivial: first, there is very limited information available to enable its evaluation; second, the previous research that has attempted to determine the cost of acquiring risk information has shown that this figure varies significantly depending on the size of the firm and its operational domain. For instance, cybersecurity risk-assessment costs may vary from $1,000 to $50,000 (see, Esecurity Solutions, 2021). Kirvan (2021) reports that the hourly rate for conducting a risk assessment is in the region of $150-$400, which, considering the time needed to complete such an analysis (about 40 days; see Biscoe, 2021), yields a total cost of $48,000-$128,000 (assuming a typical 8-hour workday). Based on these studies, in our sensitivity analysis (described below), we set the maximum value of α to $128,000 (or 1.28 units measured in hundreds of thousands of dollars). However, we first illustrate the implementation of our algorithm for the case where the values of α and β are fixed, with $\alpha = 0.2$ and $\beta = 3$. Table 6 shows the value of the objective as a function of the decision variable *f* given the data presented in Table 5.

Table 6. Value of the objective $Z(f)$ as a function of the decision variable f

f	$Z(f)$	f	$Z(f)$	f	$Z(f)$
0	1.000000	7	1.005809	14	1.063628
1	0.999978	8	1.009250	15	1.079311
2	1.000098	9	1.014639	16	1.097320
3	1.000255	10	1.020917	17	1.117492
4	0.999784	11	1.028879	18	1.140301
5	1.001238	12	1.038751	19	1.165935
6	1.003182	13	1.050435	20	1.194460

To evaluate the effectiveness of the proposed stopping-rule algorithm, we introduce the set of performance measures defined in Table 7.

Table 7. Performance measures: $\rho_{\mathrm{model}}, \rho_N, \rho_{actual}$

Measure	Meaning
$\rho_{\mathrm{model}} = \frac{Z(f^{\mathrm{model}})}{Z(f^{antic})} - 1$	The gap (in %) between the objective associated with the stopping rule, i.e., $Z(f^{\mathrm{model}})$, and the anticipative optimum, i.e., $Z(f^{antic})$ *
$\rho_N = \frac{Z(f^N)}{Z(f^{antic})} - 1$	The gap (in %) between the objective associated with seeking full information, i.e., $Z(f^N)$, and the anticipative optimum, i.e., $Z(f^{antic})$
$\rho_{actual} = \frac{Z(f^{actual})}{Z(f^{antic})} - 1$	The gap (in %) between the objective associated with seeking actual information, i.e., $Z(f^{actual})$, and the anticipative optimum, i.e., $Z(f^{antic})$ **

* The anticipated optimum, $Z(f^{antic})$, is the optimal solution that is achieved when exact information regarding the probabilities of occurrence and impacts of all risks is known in advance (e.g., from historical data), whereas $Z(f^{\mathrm{model}})$ is the objective that is achieved by implementing the proposed algorithm.

** The actual number of risk factors to be explored, i.e., f^{actual}, is the value chosen by the decision-makers. In practice, when no model is used, such a decision tends to be subjective, and thus might be far from f^{antic}.

From Table 6, it straightforwardly follows that the anticipative optimal solution (that is, the optimal solution when information about the risks is fully known) is obtained at $f^{antic} = 4$, with accordingly $Z(f^{antic}) = 0.999784$, whereas the solution that is obtained by implementing the proposed model is $f^{\mathrm{model}} = 1$, with $Z(f^{\mathrm{model}}) = 0.999978$. To evaluate f^{actual}, i.e., the number of risk factors that are explored in the real-life operation of such supply chains, a small survey was conducted among several experts employed by the Health Maintenance Organization (HMO) in Israel. The results of this survey led to $f^{actual} = 17$ which, when applied to the data in Table 6, yields $Z(f^{actual}) = 1.117492$. Note that the estimate obtained from the experts is in line with the results shown in Table 6 in the sense that f = 17 serves as a threshold value after which the objective function starts to increase more rapidly. This means that seeking additional accurate information about further risk factors would be relatively expensive. Having established that $Z(f^{antic}) = 0.999784$, $Z(f^{\mathrm{model}}) = 0.999978$, and $Z(f^{actual}) = 1.117492$, the performance measures $\rho_{\mathrm{model}}, \rho_N$ and ρ_{actual} may be calculated (see Table 8).

Table 8. Effectiveness of the proposed algorithm relative to other approaches

Measure	Deviation (%)
ρ_{model}	0.019%
ρ_N	19.472%
ρ_{actual}	11.773%

Table 8 indicates that the suggested stopping rule has the potential to obtain a solution with nearly the same objective value as the anticipative optimal solution, the percentage difference being just 0.019%. However, the anticipative optimal solution effectively requires full information to be sought, which is less efficient and incurs greater monetary costs than implementing the solution obtained by the proposed model (specifically, the strategy of seeking full, accurate information is 1.194 times more expensive). Table 8 also illustrates the superiority of the proposed model over current practice, where information about 17 risk factors is obtained. Specifically, the objective under this strategy is approximately 11.773% greater than under the proposed model (i.e., stopping rule).

Naturally, different pharmaceutical supply chains are characterized by different values of the parameters α and β. To investigate the effect of varying these parameters on the performance measures presented above, a sensitivity analysis was conducted. In this analysis, α was varied between 0.0128 and 1.28, in steps of 0.0128, while β took on values between 0.1 and 4, in increments of 0.1. In total, 4,000 different scenarios were generated. Figures 1 and 2 depict the impact of parameters α and β on the performance measures ρ_N and ρ_{actual}, respectively.

The results of the sensitivity analysis show that in approximately 94% of scenarios, the optimal solution determined by the proposed algorithm (stopping rule) coincides with the anticipative optimal solution (i.e., $\rho_{model} = 0\%$). The largest deviation is observed for the case where $\alpha = 0.0128$ and $\beta = 1.8$, with accordingly $\rho_{model} = 0.111\%$. Figure 1 shows that the performance measure ρ_N attains its maximum value of $\rho_N = 127.454\%$ for the case where $\alpha = 1.28$ and $\beta = 4$, whereas its minimum value, $\rho_N = 0.726\%$, occurs when $\alpha = 0.0128$ and β falls in the interval between 0.1 and 1.2, i.e., $\beta \in [0.1, 1.2]$. The last performance indicator, ρ_{actual}, reaches its maximum value, $\rho_{actual} = 125.403\%$, when $\alpha = 1.28$ and $\beta = 0.1$, and its minimum value (of $\rho_{actual} = 0.465\%$) when $\alpha = 0.0128$ and $\beta = 4$ (see Figure 2).

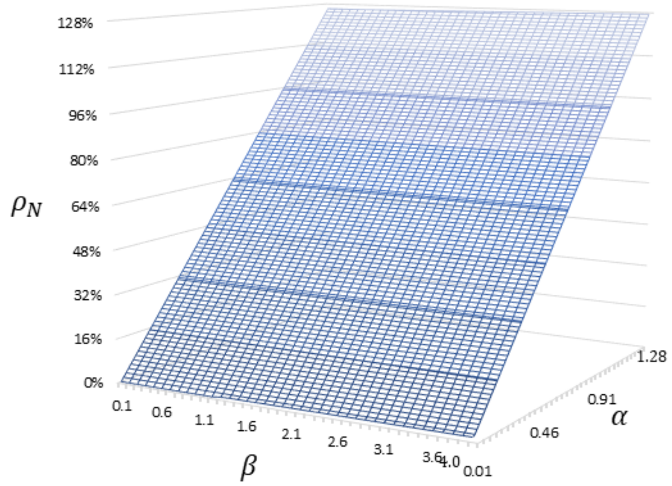

Figure 1. The effects of α and β on ρ_N

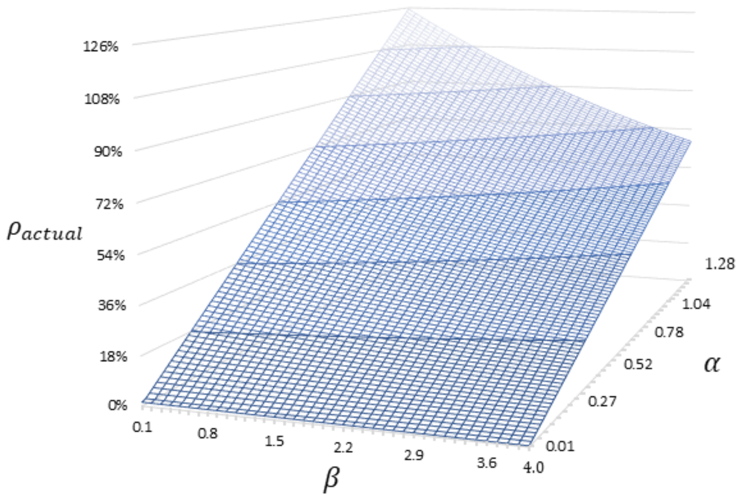

Figure 2. The effects of α and β on ρ_{actual}

It may be surprising to some that, as shown in Figures 1 and 2, α has a much stronger influence on the performance measures ρ_N and ρ_{actual} than β. In particular, ρ_N increases almost linearly with α, but remains relatively unchanged as a function of β (see Figure 1). A more complicated pattern is observed for the performance measure ρ_{actual} (see Figure 2); for a given value of α, ρ_{actual} exponentially decreases with β. Since parameter β represents a power in the proposed objective, its value is likely to be relatively small for most organizations (accordingly, a maximum value of less than 4 was used to conduct the sensitivity analysis). Consequently, we expect that the value of the performance measure ρ_{actual} will be greater than the value of ρ_{model}.

4.2. The effect of changing the sequence of risk factors

The above results were obtained under the assumption that the risks are sequenced according to the order presented in Table 4. To rule out the possibility that the conclusions reached in the previous subsection are valid only for that specific sequence, we generated 100,000 random sequences of the same set of risks, and present the results in Table 9.

Table 9. The effect of changing the order of risk factors (summary measures for 100,000 random sequences)

	Proposed model	Full information	Actual practice
Average performance (in %)	$\rho_{model} = 0.00442$	$\rho_N = 19.509$	$\rho_{actual} = 11.846$
Poorest performance (in %)	$\rho_{model} = 0.16269$	$\rho_N = 19.708$	$\rho_{actual} = 12.084$
Proportion (in %) of sequences for which the objective is no more than 100% greater than the anticipative optimum	100	100	100
Proportion (in %) of sequences for which the objective is no more than 80% greater than the anticipative optimum	100	100	100
Proportion (in %) of sequences for which the objective is no more than 60% greater than the anticipative optimum	100	100	100
Proportion (in %) of sequences for which the objective is no more than 40% greater than the anticipative optimum	100	100	100
Proportion (in %) of sequences for which the objective is no more than 20% greater than the anticipative optimum	100	100	100
Proportion (in %) of sequences for which the objective is no more than 10% greater than the anticipative optimum	100	0	0
Proportion (in %) of sequences for which the objective is no more than 5%	100	0	0

	Proposed model	Full information	Actual practice
greater than the anticipative optimum			
Proportion (in %) of sequences for which the objective is no more than 1% greater than the anticipative optimum	100	0	0
Proportion (in %) of sequences for which the objective is no more than 0.1% greater than the anticipative optimum	99.681	0	0
Proportion (in %) of sequences for which the objective is no more than 0.01% greater than the anticipative optimum	91.759	0	0
Proportion (in %) of sequences for which the objective is equal to the anticipative optimum	89.177	0	0

The results in Table 9 support our earlier conclusions by showing that the specific sequence of the risk factors has a relatively small effect on the performance measures. In particular, in more than 89% of all sequences, the objective achieved by the proposed model matches that of the anticipative optimum. In 100% of all sequences, the proposed model obtains an objective that is no more than 1% higher (i.e., more expensive) than the objective of the anticipative optimum. Table 9 also indicates that the strategy of seeking information about all risks, as well as the current strategy used in practice, are relatively inefficient. For these two approaches, not a single sequence achieves an objective that is even 1% lower than that of the anticipative optimum.

5. Application in a generalized green supply chain: method and results

Continuous depletion of natural resources during recent decades, coupled with increased air, water, and soil pollution, has caused rapid deterioration in environmental sustainability. Consequently, the frequency of natural disasters (e.g., earthquakes, floods) has substantially increased, potable water has become increasingly scarce, and living conditions have deteriorated. As a part of the worldwide effort to improve the current situation, traditional supply chains have been forced to revise their operation by adopting new environmentally-oriented rules such as environmental purchasing, environmentally-oriented distribution, and reverse logistics (see Mangla et al., 2018). By accepting such standards, firms extend their responsibility beyond the classical supply-chain operational aspects (e.g., avoiding delivery disruptions, ensuring sufficient inventory levels) to novel, environmentally-oriented issues (e.g., reducing pollution, product waste, and packaging). Non-compliance with these requirements may cause losses of a financial nature or cause significant reputational damage. Since the available assets of firms are limited, the main purpose of this subsection is to demonstrate how implementing the proposed stopping-rule algorithm may assist a firm in deciding which environmental supply-chain issues should be addressed and which may be neglected. Non-compliance with an environmental rule may be characterized by two factors: the likelihood of the ensuing adverse event (e.g., excessive packaging) and the corresponding impact of the event on the firm. Accordingly, we treat these adverse events as risk factors.

We begin by identifying the main sources of risk faced by a firm when operating a generalized green supply chain (see Column #1 of Table 10). These risk factors were obtained by reviewing the relevant literature, particularly the studies by Giannakis & Papadopoulos (2016), Mangla et al. (2018), de Oliveira et al. (2022), Kumar et al. (2019), and Medina-Serrano et al. (2021). The reader is referred to Section 2.3.2 for detailed descriptions of these papers. Note that rather than focusing on green-related risks in a specific industry, we identified the main risk factors based on a review of studies from various sectors of the economy (e.g., pharmaceutical, plastics industry). This approach was taken because our goal was to investigate the effectiveness of the proposed method for a *generalized* green supply chain, thereby increasing the significance of our findings. Such an approach has been employed in many previous studies. For instance, Pan & Wu (2014) used generalized stochastic Petri nets (GSPN) to simulate a generalized green supply-chain network, while Wibowo (2013) developed a fuzzy multi-attribute decision-making approach to tackle a generalized green supply-chain performance-evaluation problem. Each risk factor presented in Table 10 is accompanied by two attributes: (a) the likelihood of occurrence and (b) the corresponding impact (see Columns #2 and #3, respectively). The data in these columns are presented in a scaled form with values ranging from 1 (very low probability of occurrence or insignificant impact) to 10 (very high probability of occurrence or substantial impact). The last column in this table (i.e., #4) is calculated by multiplying Column #2 by Column #3 and reflects the expected impact.

Table 10. Generalized green supply-chain risks

Risk number	Risk factor f (#1)	Acquired data		Expected impact (#4)
		Probability of occurrence (#2)	Impact (#3)	
1	(1) Disturbances in supplying green raw materials	3.0	7.0	21.0
2	(2) Lack of collaborative relationships in adopting green practices	3.0	5.0	15.0
3	(3) Excessive or unnecessary packaging	5.5	6.7	36.9
4	(4) Failure of government policies (lack of environmental policies and regulations)	4.0	5.0	20.0
5	(5) Deficiency in the green technology level required to achieve “going green” policies	7.0	8.0	56.0
6	(6) Lack of environmental	6.0	7.0	42.0

Risk number	Risk factor f (#1)	Acquired data		Expected impact (#4)
		Probability of occurrence (#2)	Impact (#3)	
	standards and certifications (e.g., ISO, RoHS)			
7	(7) Scarcity of labor with the necessary knowledge in green operations and activities	7.0	9.0	63.0
8	(8) Cost ineffective development (adoption of more expensive green practices)	8.0	7.0	56.0
9	(9) Reverse logistics related disruptions	8.0	8.0	64.0
10	(10) Green issues while closing the loop of the GSC (gate-keeping policy issues regarding the returned products)	8.0	9.0	72.0
11	(11) Environmental accidents (e.g., fires, explosions)	8.5	4.9	41.7
12	(12) Pollution (air, water, soil)	8.0	6.9	55.2
13	(13) Product waste	5.6	5.0	28.0
14	(14) Disturbances due to climate change (e.g., earthquakes, floods)	8.8	5.3	46.6
15	(15) Inventory related disruptions (e.g., product unavailability)	8.0	3.0	24.0
16	(16) Inefficient use of materials and energy	7.0	6.9	48.3
17	(17) Legal risks (e.g., litigation claims)	6.9	3.0	20.7
18	(18) Water scarcity	6.8	4.0	27.2
19	(19) Limited flexibility/Capacity disruptions	8.0	6.0	48.0
20	(20) Market dynamics (e.g., financial crisis, boycotts)	8.5	5.3	45.1

The identification and characterization of the relevant risk factors is just the first step in the risk-management procedure. Since the available resources of a firm for risk mitigation are limited, decision-makers need to decide how to optimally use them – that is, which risks should be addressed and which may be overlooked (due to either low probability of occurrence or insignificant damage). Various techniques have been developed to achieve this goal. Among the most popular and widely used is the Pareto rule (see, for instance, Giannakis & Papadopoulos, 2016), according to which all risks faced by the firms are sorted in descending order of expected impact. That is, the higher the expected impact of the risk, the higher its rank in the risk hierarchy, and consequently, the greater the effort that should be expended in mitigating it. It is practical to separate the ranked list into a number of groups (e.g., three), where the first group (named A) includes the risks that together account for approximately 80% of the total impact, the second group (named B) includes the risks that will increase the accumulated impact to approximately 95%, and the last group (named C) consists of the remaining risks. Such a practice is widely used in inventory management and many other areas (see, for instance, Wild, 2017). Applying the Pareto rule to the data in Table 10 leads to the classification of the risks presented in Table 11.

Table 11. Pareto classification

Risk factor f (#1)	Expected impact (in descending order) (#2)	Aggregated Impact (#3)	Aggregated impact as a % of the total impact (#4)	Group (#5)
10	72	72	8.7%	A
9	64	136	16.4%	A
7	63	199	24.0%	A
5	56	255	30.7%	A
8	56	311	37.4%	A
12	55.2	366.2	44.1%	A
16	48.3	414.5	49.9%	A
19	48	462.5	55.7%	A
14	46.64	509.14	61.3%	A
20	45.05	554.19	66.7%	A
6	42	596.19	71.8%	A
11	41.65	637.84	76.8%	A
3	36.85	674.69	81.2%	A
13	28	702.69	84.6%	B
18	27.2	729.89	87.9%	B
15	24	753.89	90.8%	B
1	21	774.89	93.3%	B
17	20.7	795.59	95.8%	B
4	20	815.59	98.2%	C
2	15	830.59	100.0%	C

Having completed this step, the decision-makers are aware of which risks are most dangerous for the firm (i.e., group A) and which may be neglected if the available resources are not sufficient (i.e., groups B-C). The simplicity and efficiency of the Pareto rule have not been called into question in the risk-management literature, and so the legitimate question arises: how does the proposed stopping rule compare with the Pareto rule, both in terms of performance and methodology?

For its successful implementation, the Pareto method requires as input all relevant data regarding a given risk factor, i.e., its probability of occurrence and its impact. However, in practice, it is highly unlikely that these data are known a priori for all risk factors. Usually, the firm needs to expend considerable effort in acquiring such information. Given that the total budget allocated to risk management tends to be limited, the resources available to mitigate risk will be diminished due to the substantial prior investment in revealing accurate information about all risks. The lack of resources for risk prevention or elimination could cause the firm to suffer losses if untreated risks are realized. For this reason, in contrast to the Pareto method, the proposed algorithm is based on the premise that revealing information about only a subset of the entire set of risks is more efficient. To illustrate this claim, we conduct a numerical experiment based on the data presented in Table 12.

Table 12. Input data for comparison between proposed algorithm and Pareto rule

Parameter	Description	Initial value
β	Coefficient used to characterize the specifications of a given supply chain	3
TB_1	Theoretical expenditure associated with acquiring accurate information regarding the probabilities of occurrence and severities of all risk factors (N)	3.5*
TB_2	Total costs associated with the efforts toward avoiding or reducing the consequences of all risk factors (N)	5.4*
TB	Total available budget allocated by the firm for risk management, $TB \le TB_1 + TB_2$	7.1*
ED_i	Expected impact of untreated risk i , $i \in [1..N]$	See Column #4 in Table 10

* Stated in conventional monetary units (depending on the firm's size, these units may vary from thousands to hundreds of thousands of dollars)

Recall that the goal of the decision-makers is to decide how to optimally allocate a limited budget, TB, such that the overall expenditure (denoted by TC) associated with risk management will be minimized, where TC includes the costs of: (a) acquiring exact information (i.e., the probability of occurrence and impact) for f risks, $f \le N$, where f is an unknown that needs to be determined; (b) implementing mitigation strategies for f_1 risk factors, $f_1 \le f$, where f_1 is also an unknown that needs to be determined; and (c) the expected damage resulting from the remaining $N - f_1$ untreated risks. In cost terms, the three components of TC may be expressed as $TB_1\left(\frac{f}{N}\right)^{\beta}$ (see equation (1) wherein $\alpha = TB_1$), $TB_2\left(\frac{f_1}{N}\right)$, and $\sum_{i=f_1+1}^{N} ED_i$, respectively. Given that f and f_1 should be chosen so as to minimize TC subject to the limited budget TB, the following mathematical model represents our formulation:

$$Min\ \ TC(f\,,\,f_1)=TB_1\left(\frac{f}{N}\right)^{\beta}+TB_2\left(\frac{f_1}{N}\right)+\sum_{i=f_1+1}^{N}ED_i$$

$$s.t \tag{4}$$

$$TB_1\left(\frac{f}{N}\right)^{\beta}+TB_2\left(\frac{f_1}{N}\right)\le TB$$

Based on model (4), we first calculate $TC(f\,,\,f_1)$ for the Pareto rule. Recall again that for Pareto implementation, accurate information about all risk factors needs to be known in advance. That is, $f=N$ which, with respect to the constraint in (4), implies that f_1 should satisfy $f_1\le\frac{(TB-TB_1)N}{TB_2}$ and $N-f_1$ risks will remain untreated. We then substitute into (4) the data given in Table 11 for TB, TB_1 and TB_2, as well as the data for ED_i from Table 10, which leads to the results summarized in Table 13. Note that for computational purposes, we express the values of the expected impact of the risk i, i.e., ED_i (see Column #4 in Table 10), in the format ED_i*10^{-2}.

Table 13. The solution obtained using the Pareto rule

f_1 (#1)	Treated risk factors * (#2)	$TC(f^*=20,\,f_1)$ (#3)	Utilized budget (in %) $\left[TB_1+TB_2\left(\frac{f_1}{N}\right)\right]/TB$ (#4)
1	10	11.356	53.1%
2	10, 9	10.986	56.9%
3	10, 9, 7	10.626	60.7%
4	10, 9, 7, 5	10.336	64.5%
5	10, 9, 7, 5, 8	10.046	68.3%
6	10, 9, 7, 5, 8, 12	9.764	72.1%
7	10, 9, 7, 5, 8, 12, 16	9.551	75.9%
8	10, 9, 7, 5, 8, 12, 16, 19	9.341	79.7%
9	10, 9, 7, 5, 8, 12, 16, 19, 14	9.145	83.5%
10	10, 9, 7, 5, 8, 12, 16, 19, 14, 20	8.964	87.3%
11	10, 9, 7, 5, 8, 12, 16, 19, 14, 20, 6	8.814	91.1%
12	10, 9, 7, 5, 8, 12, 16, 19, 14, 20, 6, 11	8.668	94.9%
13	10, 9, 7, 5, 8, 12, 16, 19, 14, 20, 6, 11, 3	8.569	98.7%

* The risks and their corresponding order are the same as in Table 10. Note that the description of each risk may be found in Column #1 of Table 10.

The results in Table 13 may be interpreted as follows: Assume that the firm decides to allocate a total budget of $TB=7.1$ (see Table 12) for the task of risk management. Since the implementation of the Pareto rule requires that $f^*=N=20$, this means that the firm needs to pay a total of $TB_1=3.5$ (see Table

12) to acquire accurate information about all risks. Consequently, the assets that remain available for mitigation efforts are reduced to $TB - TB_1 = 3.6$. Given that the total costs associated with the efforts toward avoiding/reducing the consequences of all risk factors is $TB_2 = 5.4$ (see Table 12), and since $TB - TB_1 = 3.6$, the firm is able to deal with a maximum of $f_1 = 13$ risks, thereby utilizing 98.7% of its total budget (see Column #4 in Table 13). Referring to Table 11, this means that the firm can, in principle, treat all risks with the highest expected impact, i.e., those that belong to risk-group *A*, while absorbing the expected damage from the remaining risks. The decision-makers may also choose to apply mitigation efforts to fewer risk factors, i.e., $f_1 < 13$, which, on the one hand, will reduce the cost $TB_2\left(\frac{f_1}{N}\right)$, while on the other hand, will lead to an increase in the expenses associated with the expected impact of the untreated risks, i.e., $\sum_{i=f_1^*+1}^{N} ED_i$. Obviously, different choices of f_1 will result in different values of the objective function $TC(f^* = 20, f_1)$, as shown in Column #3 of Table 13. The table also shows that increasing the budget utilization (Column #4) achieves lower overall costs (Column #3). In particular, to minimize the total cost, the decision-makers should choose $f_1^* = 13$, associated with the highest budget utilization.

Next, we calculate the objective function $TC(f, f_1)$ under the application of the proposed stopping rule. To this end, based on Table 10, we first compute the normalized impact, i.e., r_i, of each risk factor. The results are presented in Table 14, wherein the order of the risks is the same as in Table 10.

Table 14. Risk factors and their normalized impacts under full information

f	Normalized impact r_i	f	Normalized impact r_i
1	0.025283	11	0.050145
2	0.018059	12	0.066459
3	0.044366	13	0.033711
4	0.024079	14	0.056153
5	0.067422	15	0.028895
6	0.050566	16	0.058151
7	0.075850	17	0.024922
8	0.067422	18	0.032748
9	0.077054	19	0.057790
10	0.086685	20	0.054240

Then, given that $\alpha = TB_1 = 3.5$ and $\beta = 3$ (see Table 12), and using equation (1), we compute the value of the objective function $Z(f)$, which is shown in Table 15.

Table 15. Value of the objective $Z(f)$

f	$Z(f)$	f	$Z(f)$	f	$Z(f)$
0	1.000000	7	1.136824	14	2.178037
1	0.997835	8	1.210144	15	2.453100
2	0.995898	9	1.303187	16	2.767857
3	1.003940	10	1.417610	17	3.123493
4	1.016525	11	1.562365	18	3.524221
5	1.042785	12	1.734508	19	3.973515
6	1.082540	13	1.939259	20	4.472702

From Table 15, it is immediately apparent that the objective function attains its minimal value when $f^* = 2$, with $Z(f^*) = 0.995898$. It is worth noting that the optimal solution of the model coincides with the optimal anticipative solution (that is, the solution when full data about the probabilities of occurrence and severities of the risks are known in advance). The solution means that information is sought, and mitigation efforts are expended, for the first two risks only. To calculate the total cost of such a solution, we again use the objective function in (4). In particular, substituting $f^* = f_1^* = 2$ into (4) yields $TC(f^* = 2, f_1^* = 2) = 8.489$. Note also that $f^* = f_1^* = 2$ constitutes a feasible solution since the constraint in (4) is satisfied.

One can easily verify that the solution determined by the proposed stopping rule is superior to that obtained by implementing the Pareto rule. To illustrate this, we compute the percentage difference between the objective function obtained using the Pareto rule (which varies as a function of f_1^*), i.e., $TC(f^* = 20, f_1^*)$, and the objective function achieved by the proposed algorithm, $TC(f^* = 2, f_1^* = 2) = 8.489$. The results are presented in Table 16. Interestingly, the budget utilization $\left[TB_1\left(\frac{f=2}{N}\right)^{\beta} + TB_2\left(\frac{f_1=2}{N}\right)\right]/TB$ for the solution based on the stopping rule is only 7.65%, which is considerably lower than the budget utilization when employing the benchmark method, i.e., 98.7%.

It can be seen from Table 11 that the risk classification for this example does not follow a clear Pareto principle in which approximately 80% of the consequences originate from 20% of the causes (see, for instance, Kim et al., 2017 and Ziyadin et al., 2020) among many others). According to Giannakis & Papadopoulos (2016), situations such as that shown in Table 11 may arise when supply-chain risks are diverse and when multiple decision-makers take part in the estimation of risk consequences. Under these circumstances, the perceived importance of the risks becomes homogeneously spread, and accordingly, the Pareto rule is violated. This means that in some real-life situations, the relative size of set A is likely to be much smaller than in our example. Consequently, the gap between the two methods would be even greater than 0.94% (since f_1^* would be smaller than 13) – probably in the region of 15%.

Table 16. Superiority of the proposed algorithm over the Pareto rule

Pareto rule		$\frac{TC(f^* = 20,\ f_1^*)}{TC(f^* = 2,\ f_1^* = 2)} - 1$ (in %)
f_1^*	$TC(f^* = 20,\ f_1^*)$	
1	11.356	33.77%
2	10.986	29.41%
3	10.626	25.17%
4	10.336	21.75%
5	10.046	18.33%
6	9.764	15.01%
7	9.551	12.50%
8	9.341	10.03%
9	9.145	7.72%
10	8.964	5.59%
11	8.814	3.82%
12	8.668	2.10%
13	8.569	0.94%

6. Discussion

6.1. Summary and conclusions

An unpredictable and frequently changing business environment requires firms to be aware of the current risks that may have a significant impact on their operation. Addressing all risks is not cost effective and is also likely to be infeasible. We contribute to the relatively modest literature presenting empirical evidence on efficient and effective risk mitigation in supply chains under the assumption of a limited budget. By assuming a continuous setting, we develop a relatively simple stopping rule in which the algorithm stops acquiring exact information about risk factors at the point where acquiring such information for the subsequent risk factor would cause the cost objective to increase for the first time.

Our computational analyses indicate that the proposed model is a highly effective tool that achieves superior results to other techniques utilized in the domain of risk management. In particular, we find that the total cost of risk management is lower for the proposed model than for the widely used Pareto algorithm. Moreover, we find that for approximately 94% of all investigated cases, the stopping-rule algorithm coincides with the anticipative optimal solution, which is never worse than the optimal solution. By generating 100,000 random sequences of the same set of risks, we show that in 99.681 % of sequences, the objective is no more than 0.1% greater than the anticipative optimum. The conclusion is that changing the sequence of risk factors has a relatively small effect on the results.

6.2. Managerial implications

It may be surprising to some to learn that, for both of the applications investigated in this study, the optimal number of risk factors to be fully explored is, according to our model, very small. This not only results in a significant monetary saving (relative to the traditional approach), but also reduces the time spent on risk management.

Our model assumes that the risk factors should be prioritized solely on the basis of their likelihood and their impact (i.e., potential damage). Decision-makers who wish to include additional considerations (e.g., subjective preference) may alter the initial set of risk factors and run the stopping rule again. Given that our analysis shows, through the above computational runs that the specific sequence of the risk factors has a relatively small effect on the performance measures, it is expected that the efficiency of our model would not deteriorate significantly by including additional considerations.

For the generalized green supply chain, the budget utilization according to the solution based on the stopping rule is less than 10% of the budget utilization under the benchmark method. Risk-management teams may find this to be an appealing feature, especially when monetary resources are low.

6.3. Future research avenues

The stopping rule is empirically tested using real-life data gathered from the operation of pharmaceutical supply chains and supply chains with generalized, green-related risks. These two applications are characterized by numerous risk factors, and efficient management of their risks is crucial to society. Applying the proposed algorithm to other supply chains, such as perishable food or the fashion industry, would be a worthwhile avenue for future research.

The suggested stopping rule (which is effectively a substitute for the unknown optimal solution of the model) involves a very simple procedure: if the objective does not increase in value, the subsequent risk factor should be added to the list of risk factors for which full information is pursued. Thus, the complexity of the suggested algorithm is $O(N)$, meaning that many risk factors can be handled within a very short computational time. The efficiency achieved for very large projects, are suggested as avenues for future research.

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