Transportation Research Part E 163 (2022) 102759

Contents lists available at ScienceDirect

Transportation Research Part E

journal homepage: www.elsevier.com/locate/tre

A causality analysis of risks to perishable product supply chain networks during the COVID-19 outbreak era: An extended DEMATEL method under Pythagorean fuzzy environment

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A R T I C L E I N F O

Keywords:
Disaster management
Risk analysis
Pythagorean fuzzy DEMATEL
COVID-19
Pandemic outbreaks
Perishable product supply chains

A B S T R A C T

In nowadays world, firms are encountered with many challenges that can jeopardize business continuity. Recently, the coronavirus has brought some problems for supply chain networks. Remarkably, perishable product supply chain networks, such as pharmaceutical, dairy, blood, and food supply chains deal with more sophisticated situations. Generally, during pandemic outbreaks, the activities of these industries can play an influential role in society. On the one hand, products of these industries are considered to be daily necessities for living. However, on the other hand, there are many new restrictions to control the coronavirus prevalence, such as closing down all official gatherings and lessening the work hours, which subsequently affect the economic growth and gross domestic product. Therefore, risk assessment can be a useful tool to forestall side-effects of the coronavirus outbreaks on supply chain networks. To that aim, the decision-making trial and evaluation laboratory approach is used to evaluate the risks to perishable product supply chain networks during the coronavirus outbreak era. Feedback from academics was received to identify the most important risks. Then, experts in pharmaceutical, food, and dairy industries were inquired to specify the interrelations among risks. Then, Pythagorean fuzzy sets are employed in order to take the uncertainty of the experts' judgments into account. Finally, analyses demonstrated that the perishability of products, unhealthy working conditions, supply-side risks, and work-hours are highly influential risks that can easily affect other risk factors. Plus, it turned out that competitive risks are the most susceptive risk in the effect category. In other words, competition among perishable product supply chain networks has become even more fierce during the coronavirus outbreak era. The practical outcomes of this study provide a wide range of insights for managers and decision-makers in order to prevent risks to perishable product supply chain networks during the coronavirus outbreak era.

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https://doi.org/10.1016/j.tre.2022.102759
Received 9 April 2021; Received in revised form 1 May 2022; Accepted 19 May 2022
Available online 26 May 2022
1366-5545/

1. Introduction

Risk is a potential for undesired consequences that emerges from an incident or activity (Prakash et al., 2017). The uncertain nature of activities, globalization, new legislations, and financial crises have made the supply chain networks prone to a broad range of risks. Generally, risk in the supply chain management context emerges as a change in the distribution of possible outcomes, their probabilities, as well as their subjective values (Lavastre et al., 2012). Plus, short product shelf life and an increase in demand have made supply chain management more sophisticated (Tang and Nurmaya Musa, 2011). In general, a product is called perishable if at least one of the following conditions holds for it: 1) product deteriorates 2) product's functionality mitigation has drastic subsequences 3) product's value reduces over time (Jouzdani and Govindan, 2021). By the same token, among all supply chain networks, perishable product supply chain networks' (PPSCN) activities are significantly crucial because they provide preliminary needs of human-being. What makes the activity of PPSCNs more prone to various kinds of risks is the limited shelf life since perishable products easily deteriorate during the logistical procedures of a supply chain network (Liu et al., 2018). To avoid these risks, managers and academics try to provide a supply chain risk management framework. Supply chain risk management contains three major steps, including risk identification, risk analysis, and providing a proper response to risks according to the analysis. Risk identification and risk analysis are two major strides in supply chain risk management. Having these two strides done, companies would be able to make proper plans in order to cope with likely risks. Supply chain risk management has a critical role in mitigating accidental deviations (Fazli et al., 2015). It should be noticed that interdependency brings about risks in supply chain networks. So, identifying cause-and-effect relations among likely risks to supply chain networks is critical since concealed influences of a particular risk are linked with other risks that may have negative consequences (Govindan and Chaudhuri, 2016). Hence, this is important to analyze cause-and-effect relations among risks to supply chain networks in order to prevent a certain risk as well as its hidden influences on other risks. Reviewing the literature, it can be grasped that not much attention has been paid to analyze cause-and-effect relations among risks to supply chain networks. From a few papers that have studied interdependency between risks to supply chain networks, studies by Fazli et al. (2015) and Mangla et al. (2016) can be mentioned. As mentioned earlier, PPSCNs deal with a complicated situation owing to uncertain demand, the short shelf life of products, high deterioration rate, etc. (Lusiantoro et al., 2018). However, yet, no study to date has investigated interdependency between risks to perishable product industries. Notwithstanding, several risks can arise as side-effects of a specific crisis, which have been neglected in the literature. Thus, risk analysis during a disaster is another gap that has not been pointed out by any former study. Disaster means phenomenal incidents, such as earthquakes, floods, pandemic diseases, etc., which happen suddenly such that its intensity may enhance (Govindan et al., 2020). As a threat to humanity, a disaster may take plenty of lives. Moreover, a disaster acts as a brake pedal to bring economic growth to a halt; even worse, it may lead to an economic downturn. Since December 2019, coronavirus has emerged as the most hazardous disease. In March 2020, World Health Organization (WHO) characterized the coronavirus disease as a pandemic. Since then, governments were obliged to react by setting some new restrictions in order to control coronavirus prevalence. Epidemics, unlike other sorts of risks, begin on a small scale and then, out of a sudden, proliferate so that they can spread across large areas of the world in a few weeks (Ivanov, 2020a). Up to March 2022, the coronavirus disease 2019 (COVID-19) has affected virtually 438 million people and took the lives of about 5.9 million people all around the world (WHO, 2022). In reply thereto, new restrictions have been set to deal with COVID-19 spread. Undoubtedly, restrictions have posed problems for all supply chain networks. The COVID-19 plainly indicates the lack of resiliency in supply chain networks (Golan et al., 2020). All in all, in light of what explained, studying risks to PPSCNs is very vital and, the COVID-19 outbreak redoubled the importance of it. So, this study tries to make the literature move forward by analyzing interrelations among risks to PPSCNs during the COVID-19 outbreak era.

Undeniably, COVID-19 has touched our lives and businesses. It has been reported that plenty of facilities worldwide, which belong to the largest companies, have been drastically touched by COVID-19. Besides, with an increase in hospitalized cases of COVID-19 across Europe and the United States, the transport of raw material and products has been occluded all around the world (Paul and Chowdhury, 2021). Given the above-explained problems, the question is raised about how managers can decrease the side-effects of the COVID-19 on businesses. Surely, the answer would be a precise risk assessment. Risk management involves identification, analysis, response to risks based on analysis (Mousavi et al., 2011). In order to successfully respond to risks, at first, risk identification and analysis must be performed. Therefore, this paper analyzes interrelations among risks that arise from the COVID-19 outbreak to provide practical insights for decision-makers such that they act preparedly in the face of the severity of COVID-19 side-effects on PPSCNs. According to our knowledge, no previous study has represented a comprehensive framework to analyze interrelations among risks to PPSCNs during a disaster. Besides, the COVID-19 pandemic has drastically touched supply chain networks; so, plenty of supply chain scholars have turned their attention to issues related to the COVID-19 pandemic (Chowdhury et al., 2021). Thus, specifically, this study tries to advance the supply chain risk management literature by responding to the following research questions.

- What are the most influential risks to PPSCNs during the COVID-19 outbreak era?
- How risks to PPSCNs can affect each other during the COVID-19 outbreak era?
- What are the most susceptible risks to PPSCNs during the COVID-19 outbreak era?

In order to respond research questions, risks to PPSCNs are identified utilizing academics' feedback. Next, the decision-making trial and evaluation laboratory (DEMATEL) method is used to evaluate the interrelationships among risks to PPSCNs during the COVID-19 outbreak. The DEMATEL technique portrays the effect of factors, depicts causal relations, and analyzes dependent factors (Du and Li, 2021). In the literature, the DEMATEL technique has been employed in a wide range of fields, i.e., risk analysis, hotel service, e-learning evaluation, supplier selection, etc. (Govindan et al., 2015; Kaya and Yet, 2019; Yazdi et al., 2020). The DEMATEL method has a lucid superiority to other pairwise comparison methods. In the DEMATEL method's hierarchical structure, each factor can affect other factors and be affected by each of them, whether the factors are at the same level or not. Therefore, the DEMATEL method allows decision-makers to decide according to paired comparisons and feedback of relations, which is a significant superiority of this method. Besides, the DEMATEL method accepts all transferable relations and can sight every possible feedback, which is another superiority of the DEMATEL method compared to others (Shahbodaghlou and Samani, 2012; Mostafaeipour et al., 2019). In other words, the DEMATEL method can generate the effect relation map of factors, which provides the opportunity to perform a causal analysis among various factors (Kou et al., 2021). Next, experts from different PPSCNs were asked to assess the interrelationship among risks. Real-world situation is entwined with uncertainty such that this vague nature of the real-world condition impacts the decision-making process. A way to overcome vagueness in the decision-making process is to express favorites using fuzzy sets rather than binary logic (Govindan et al., 2015). Furthermore, crisp numbers cannot express the ambiguity of experts' views. Given that using the discrete scale, the uncertainty related to one's judgment cannot be considered (Paksoy et al., 2012), so, it is rational to use fuzzy sets. In this paper, we use Pythagorean fuzzy sets introduced by Yager (2013). Reviewing recent studies reveals that Pythagorean fuzzy sets can deal with the ambiguous nature of data very well (Yu et al., 2019; Yazdi et al., 2020). Thus, Pythagorean fuzzy sets are employed in order to tackle the ambiguous nature of the expert elicitation methods.

To our knowledge, no previous paper has analyzed the interrelations among risks to PPSCNs during the COVID-19 outbreak era. Hence, the primary contributions of this study that make a clear and pellucid distinction between this study and any other related study are as follows:

- Providing a proper framework for risk analysis during the COVID-19 outbreak era;
- Using academics' feedback to identify the most influential risks to PPSCNs during the era of COVID-19 outbreak;
- Employing an extended DEMATEL approach;
- Inquiring experts' opinions from various perishable product industries on specifying the interrelationships among risks;
- Utilizing Pythagorean fuzzy sets to deal with the ambiguity of experts' opinions.

The residue of this paper is organized as follows: Section 2 is dedicated to the literature review. Pythagorean fuzzy DEMATEL

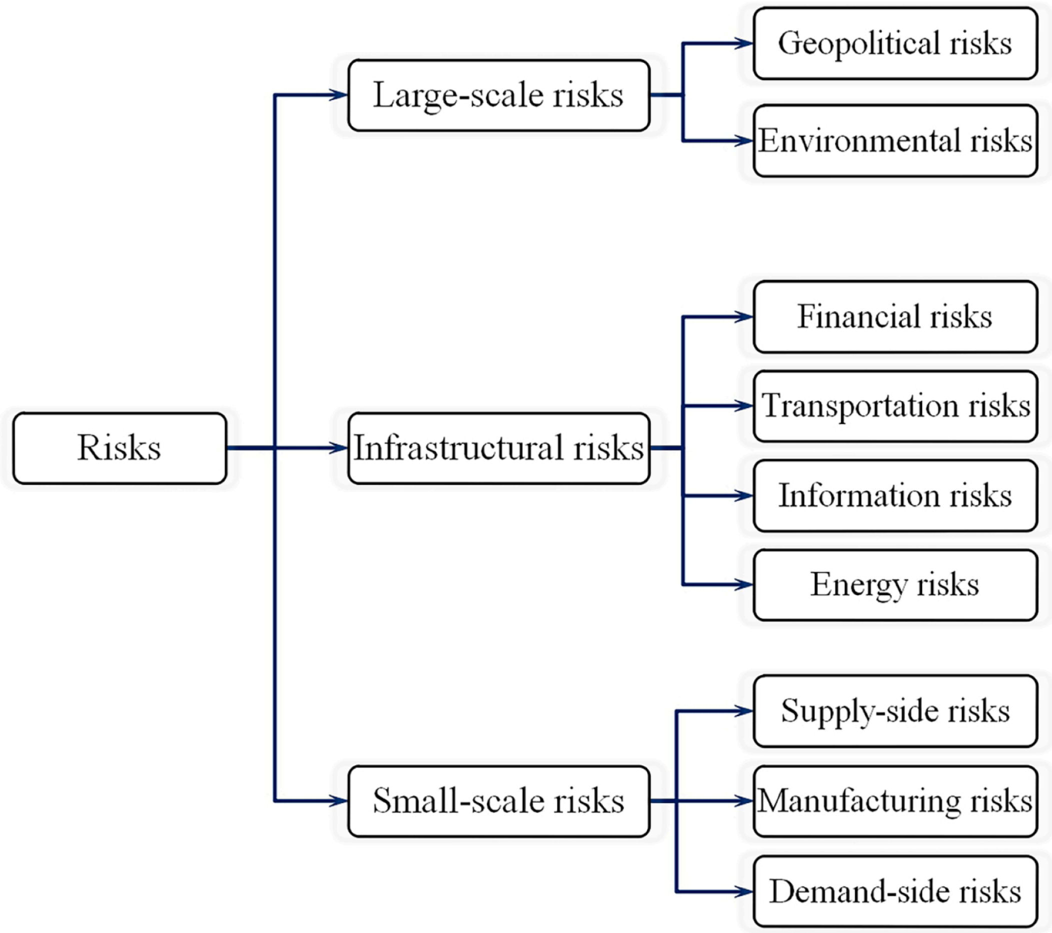

Fig. 1. A comprehensive classification of supply chain risks (extended from the study by Ho et al. 2015).

approach is included in Section 3, while Section 4 provides the case study and its results. Section 5 represents discussion. Theoretical, managerial, and policy contributions are discussed in Section 6. Finally, Section 7 provides conclusions and outlooks.

2. Literature review

Generally, there are mutual interrelations between supply chain networks, society, economy, and nature (Ivanov, 2020b). Historical data suggest that disasters, including wars and pandemics, have always had considerable consequences for supply chain networks (Veselovská, 2020). Furthermore, during an epidemic outbreak, supply-side activities, markets, and infrastructure may be incurred to risk simultaneously (Ivanov, 2020a); this means a pervasive framework towards identifying every kind of risk to PPSCNs is required. Based on this argument, in this section, a brief review of different risks to PPSCNs is presented. Plus, recent literature on DEMATEL applications in risk analysis is provided. Lastly, the research gap is explained.

2.1. Risk categories

In this study, various risk factors were selected. Generally, as shown in Fig. 1, risks are divided into three main categories—large-scale risk, small-scale risks, and infrastructural risks. Likewise, each of these three categories consists of some sub-categories. From a more elaborate perspective, the main origins of supply chain risks are traced through issues associated with geopolitics, environment, financial state, transportation, information, energy, supply-side activities, demand-side activities, and manufacturing. So, sub-categories (risk factors) are extracted from each of these nine risk categories. Large-scale risks are proportionately rare and have an external origin so that they can adversely impact businesses, whereas small-scale risks contain more recurrent incidents. These risks originate from an organization's internal operations or through logistics activities in a supply chain network. Overall, large-scale risks leave a more devastating effect on supply chain networks compared to small-scale risks (Ho et al., 2015).

Table 1 provides information about identified risks to PPSCNs during the COVID-19 outbreak era. An eclectic approach was applied to catalog the risks. In other words, risks were mainly extracted from the literature, and a few of them were selected regarding emerged

Table 1
Identified risks to PPSCNs during the COVID-19 outbreak era.

No.	Sub-categories	Denotation	Reference
1	New restrictions because of the COVID-19 outbreak	R1	(Sharma et al., 2020)
2	Political instability	R2	(Moeinzadeh and Hajfathaliha, 2009; Jaberidoost et al., 2013; Samvedi et al., 2013; Ho et al., 2015; Prakash et al., 2017; Mei et al., 2020; Sharma et al., 2020)
3	War threats	R3	(Ho et al., 2015; Mei et al., 2020)
4	Natural disasters	R4	(Moeinzadeh and Hajfathaliha, 2009; Cagliano et al., 2012; Jaberidoost et al., 2013; Samvedi et al., 2013; Ho et al., 2015; Giannakis and Papadopoulos, 2016; Govindan and Chaudhuri, 2016; Prakash et al., 2017; Shenoi et al., 2018; Tarei et al., 2018)
5	Increase in COVID-19 cases	R5	(Mezghani et al., 2021; Munim et al., 2022)
6	Seasonal variations	R6	(Prakash et al., 2017)
7	Transportation incidents	R7	(Zare-Mehrjerdi and Shafiee, 2021)
8	Inadequate road infrastructure	R8	(Sharma et al., 2020)
9	IT failures	R9	(Govindan and Chaudhuri, 2016; Shenoi et al., 2018; Rostamzadeh et al., 2018)
10	Power outage	R10	(Gong et al., 2014; Shenoi et al., 2018; Moktadir et al., 2018; Yavari and Zaker, 2020)
11	Currency volatility	R11	(Cagliano et al., 2012; Jaberidoost et al., 2013; Ho et al., 2015; Govindan and Chaudhuri, 2016; Khan et al., 2021)
12	Increase in freight charges	R12	(Moktadir et al., 2018)
13	Fuel price fluctuations	R13	(Cagliano et al., 2012; Giannakis and Papadopoulos, 2016)
14	Supplier bankruptcy	R14	(Ho et al., 2015; Moktadir et al., 2018)
15	Single supply sourcing	R15	(Ho et al., 2015; Zare-Mehrjerdi and Shafiee, 2020; Zare-Mehrjerdi and Shafiee, 2021)
16	Delay in delivery of raw material	R16	(Jaberidoost et al., 2013)
17	Work-hour	R17	(Ran et al., 2020)
18	Perishability period of products	R18	(Ho et al., 2015; Shenoi et al., 2018)
19	Unhealthy working environment	R19	(Giannakis and Papadopoulos, 2016; Rostamzadeh et al. 2018)
20	Labor strike	R20	(Cagliano et al., 2012; Samvedi et al., 2013; Ho et al., 2015; Prakash et al., 2017; Khan et al., 2021)
21	Machine breakdown	R21	(Govindan and Chaudhuri, 2016; Prakash et al., 2017; Tarei et al., 2018; Moktadir et al., 2018)
22	Lean inventory	R22	(Ho et al., 2015)
23	Warehouse disruption	R23	(Ho et al., 2015; Govindan and Chaudhuri, 2016; Rostamzadeh et al., 2018)
24	Labor shortages because of being infected with COVID-19	R24	(Nagurney, 2021)
25	Demand uncertainty	R25	(Chen and Seshadri, 2009; Jaberidoost et al., 2013; Prakash et al., 2017; Moktadir et al., 2018; Özceylan et al., 2019; Sharma et al., 2020; Zare-Mehrjerdi and Shafiee, 2020; Zare-Mehrjerdi and Shafiee, 2021)
26	Changes in consumer tastes	R26	(Moeinzadeh and Hajfathaliha, 2009; Samvedi et al., 2013; Tarei et al., 2018)
27	Competitive risks	R27	(Ho et al., 2015; Prakash et al., 2017; Tarei et al., 2018; Moktadir et al., 2018)
28	Distribution network breakdown	R28	(Ho et al., 2015; Tarei et al., 2018; Sharma et al., 2020)
29	Market share reduction	R29	(Prakash et al., 2017; Rostamzadeh et al., 2018)

conditions during the COVID-19 outbreak. Thus, a meticulous identification has gone into gathering the most critical risks to PPSCNs. In the end, feedback from the academics sealed the list.

2.1.1. Large-scale risks

Generally, large-scale risks are divided into two categories, including geopolitical risks and environmental risks. The geopolitical risks are defined as acts of wars and tensions among countries in a way that touches the peaceful state of international relationships (Mei et al., 2020). The simultaneousness of the geopolitical risks and other types of risk will be even more problematic. As a matter of fact, geopolitical risks exacerbate the harmful effects of other risks and take it to a precarious state. Lately, restriction as a sort of the geopolitical risk has become problematic. It has been reported that the shutdown of Chinese factories and the simultaneous decrease in North American demand owing to import restrictions because of the COVID-19 outbreak have caused a shortage of empty containers, which made the backhaul trip to Asia impossible (Sharma et al., 2020). From other new restrictions, closing the airspace of countries and restricting maritime transport can be mentioned. So, this can be interpreted as the importance of consideration of the geopolitical risks as one of the main risk categories. Plus, recently, due to Russia's Invasion of Ukraine has posed several problems, such as delays in road and rail routes through Ukraine and its neighboring countries. In such a situation, decision-makers want to stay away from the battleground, so, they may choose the sea to ship the products. On the other hand, waterway routes are already under strain owing to the COVID-19 outbreak (ASCM, 2022).

Environmental risks have always been a tough and challenging problem for many organizations. Recently, with regard to the pandemic outbreak, the exponential growth of COVID-19 cases in a specific region is considered as an emerging environmental risk. In fact, pandemic outbreaks are a particular sort of supply chain risks (Ivanov, 2020a). According to recent evidence, an increase in COVID-19 cases has made governments compel manufacturers to shut the production (Munim et al., 2022). As a result, an increase in COVID-19 cases has negatively influenced the global supply chain as well as fiscal systems (Mezghani et al., 2021). From the other environmental risks, natural disasters and seasonal variations can be mentioned. Natural disasters contain different types, such as earthquakes, vast fires, volcanoes, floods, avalanches, rock-falls, landslides. In Table 1, R1 to R3 denote the geopolitical risks and R4 to R6 are the selected environmental risks to PPSCNs.

2.1.2. Infrastructural risks

The preliminary definition of infrastructure risks can be summarized as disruptive events materialized from the infrastructure such that firms require them for maintaining their operations (Fazli et al., 2015). From various sorts of infrastructure, energy, transportation, financial, and information system can be mentioned (Fazli et al., 2015; Yavari and Zaker, 2020). In general, infrastructures are vital for supply chain networks, particularly for PPSCNs. Any disruptive incident in infrastructures results in poor performance of the whole supply chain network (Yavari and Zaker, 2020). Among all infrastructures, financial issues have always played an important role in companies' performance. In this regard, Wan et al. (2019b) found that two crucial infrastructural risk factors, e.g., fuel price fluctuations and currency volatility, are among the top ten risks impacting the safety of maritime container supply chains. Recently, new changes in the economic environment have been produced as a concomitant to the pandemic outbreak. Therefore, this study concentrates on those financial risks caused by new shifts in the economic environment that dramatically affect the operation costs. The profound impacts of these risks are revealed in domestic and international dimensions (Govindan and Chaudhuri, 2016). The importance of considering these risks lies in the fact that the economic environment encounters new changes due to the COVID-19 outbreak. Hence, plenty of companies have to deal with a precarious financial state. In this study, infrastructural risk factors are shown from R7 to R13.

2.1.3. Small-scale risks

Small-scale risks have three main categories, consist of supply-side risks, manufacturing risks, and demand-side risks. Risks related to the accessibility of raw material from suppliers, which severely affect the capability of the manufacturers to satisfy the market demand, are called supply-side risks (Manuj et al., 2014). Supply-side issues are considered as one of the most common risks to supply chain networks (Shafiee et al., 2021). Since suppliers provide raw material, the supply chain network's whole performance will be disrupted in case of any incident in supplying centers, which means suppliers' activities are utterly vital. The most common supply-side risks are caused by disorders of the transport system, supplier bankruptcy, single supply sourcing, and delay in delivery of raw material. In Table 1, R14 to R16 indicate supply-side risk factors.

Furthermore, Ho et al. (2015) defined manufacturing risks as inauspicious incidents or circumstances within a company in such a way that leave profound effects on internal capability to manufacture products and services, quality and timeliness of manufacturing, and profitability. From the most critical manufacturing risks during the COVID-19 outbreak era, limited shelf life of products, unhealthy working environment, labor strike, machine breakdown, lean inventory, and warehouse disruption can be mentioned. In addition, recently, many factories decrease work hours in order to control the COVID-19 prevalence, which on the whole, mitigates gross domestic production (GDP). Thus, work-hour is considered to be a manufacturing risk. Plus, according to a recent study by Ran et al. (2020), the COVID-19 transmission rate is commensurate with work-hour. To put it into other words, a reduction in work-hour results in a lesser contagion rate. Recently, because of the pandemic outbreak, labor has become a vital factor in the performance of supply chain networks. In fact, being infected with COVID-19 has caused labor shortages (Nagurney, 2021), which has posed several difficulties for the manufacturing sector. In Table 1, R17 to R24 show the selected manufacturing risks to PPSCNs.

Demand-side risks are from the most usual risks that may be incurred to supply chain networks. Generally, the origin of the demand-side risks can be traced from the uncertain nature of demand (Özceylan et al., 2019), changes in customer tastes, competitors' moves, distribution center failure to dispense products to customers, and market share reduction. During the COVID-19 outbreak era, the demand-side risks have become even more probable to occur. Moreover, Chen and Seshadri (2009) claimed that PPSCNs receive a massive exposure to the demand uncertainty more than any other industry, which means studying the demand-side risks is utterly critical and momentous for PPSCNs during the pandemic outbreak. In Table 1, the selected demand-side risk factors are shown from R25 to R29.

2.2. Literature on DEMATEL applications in risk analysis

DEMATEL technique, as one of the multi-criteria decision-making (MCDM) methods, is an appropriate approach to analyze the cause-and-effect interrelationships amid different factors of a convoluted system (Ranjbar et al., 2014). To that end, the DEMATEL method has been applied, as a risk assessment tool, to various fields. Some recent studies that have used the DEMATEL approach to analyze risk factors are reviewed in the following.

Fazli et al. (2015) applied the DEMATEL technique to analyze the interrelations among risks incurred to the crude oil supply chain network. Mangla et al. (2016) tried to study the interrelations of green supply chain risks. To that aim, they applied the trapezoidal fuzzy DEMATEL approach to analyze the cause-and-effect relations among the risk factors. Govindan and Chaudhuri (2016) used the DEMATEL method to assess the interrelations among risk factors associated with activities of the 3rd party logistic service providers. They used literature to collect risk factors for the 3rd party logistic service providers. Plus, feedback from academics on risk factors was received to ensure that risk criteria are proper for their study. Then, they were given input data from experts in various industries. It should be noticed that deterministic numbers were used to express experts' opinions. Since studying the healthcare system is critical, Bhalaji et al. (2019) dedicated their study to evaluate interrelationships amid risk factors utilizing the trapezoidal fuzzy DEMATEL method. Furthermore, in order to assess the causal effect of risks to a Photovoltaic poverty alleviation project, Wu et al. (2019) developed a structural model using the intuitionistic fuzzy DEMATEL method. Moreover, Abdullah and Goh (2019) analyzed the interrelations among risk factors to solid waste management. For that purpose, they developed an extended DEMATEL approach employing Pythagorean fuzzy sets. Plus, Khan et al. (2020) performed a study to analyze causality relations among risk factors to a halal supply chain network. Besides, recently, Yazdi et al. (2020) studied the cause-and-effect relationships among offshore facility platform risks using the DEMATEL technique. They converted experts' opinions into the Pythagorean fuzzy numbers to cope with the uncertainty of input data. The reviewed studies that have used the DEMATEL method are summed up in Table 2.

2.3. Research gap

Generally, researchers have long studied different types of risks to supply chain networks. Nevertheless, pandemic-related risk management studies are still insufficient. COVID-19 spread has rekindled interest in studying the effects of epidemics on supply chain networks (Gholami-Zanjani et al., 2021; Abdolazimi et al., 2021). Nevertheless, studies related to supply chain risk management often concentrate on operational risks that influence total costs (Esper, 2021). Reviewing the literature shows a lack of studies associated with analyzing interrelations among risks to supply chain networks. Studies by Fazli et al. (2015), Mangla et al. (2016), Wan et al. (2019a), and Khan et al. (2020) are among few papers that have focused on analyzing the interrelations among risks to supply chain networks. Notwithstanding, no former study has concentrated on studying interrelations among risks to PPSCN. Also, no study has considered interrelations among risks during the COVID-19 outbreak. Hence, the current study is an attempt to bridge the gap in the literature by analyzing the interrelations among risks to PPSCN during the COVID-19 outbreak era. Furthermore, we use an extended version of the DEMATEL technique under the Pythagorean fuzzy environment in order to study interrelations among risks to PPSCNs during the COVID-19 outbreak era.

3. Methodology

Decision-making is a pervasive procedure in routine life, which can be expressed as a consequence of intellectual and reasoning processes (Zhang, 2016), which can assist managers in deciding with a more informed background. In face of convoluted systems, a comprehensive framework is required to inform managers about their decisions. To that aim, decision theory provides appropriate tools to study the consequences of decisions. Therefore, this study aims at analyzing cause-and-effect relations amid risks to PPSCNs during the pandemic outbreak era. To that aim, risk factors were selected utilizing literature review and feedback from academics. After, the extended version of the DEMATEL technique was selected to assess the interrelations among the risks. Plus, experts in various

Table 2
Reviewed papers.

Authors	Type of input data	Case
Fazli et al. (2015)	Deterministic numbers	Crude oil supply chain network
Mangla et al. (2016)	Trapezoidal fuzzy numbers	Green supply chain network
Govindan and Chaudhuri (2016)	Deterministic numbers	The 3rd party logistics service providers
Bhalaji et al. (2019)	Trapezoidal fuzzy numbers	Healthcare industry
Wu et al. (2019)	Intuitionistic fuzzy numbers	Photovoltaic poverty alleviation project
Abdullah and Goh (2019)	Pythagorean fuzzy numbers	Solid waste management
Khan et al. (2021)	Triangular fuzzy numbers	Halal supply chain network
Yazdi et al. (2020)	Pythagorean fuzzy numbers	Offshore facility platform

industries were inquired to evaluate cause-and-effect relations among risks, and their evaluations were collected as input data. The whole study framework is demonstrated in Fig. 2.

This study applies an extended version of the DEMATEL technique to analyze the cause-and-effect relations among risks to PPSCNs during the COVID-19 outbreak era. DEMATEL technique is a proper method to produce a structural model consisting of cause-and-effect relations among complicated factors. In the 1970s, the DEMATEL method was firstly developed by the Battelle Memorial Institute of Geneva. In this approach, factors are divided into two primary categories, including cause and effect. This categorizing brings about a comprehensive comprehension of the system's components and their interrelations (Govindan et al., 2015); hence, decision-makers can identify and evaluate various factors of a sophisticated system. On the other hand, studying PPSCN related risks is intricate because there are interrelations among risks. Given that the DEMATEL technique can address the intricacy associated with multiple interrelated risks, we adopt an extended version of the DEMATEL technique to analyze interrelations among risks to PPSCN.

3.1. Pythagorean fuzzy sets

In this study, experts' opinions from different PPSCNs were collected as input data. Clearly, data uncertainty causes various problems (Özmen et al., 2017). Since experts' views are ambiguous, it is recommended to use a proper method to overcome uncertainty. Generally, there is a wide range of methods to deal with data uncertainty (Zare-Mehrjerdi, 2014), including robust convex programming, stochastic programming, and fuzzy logic. However, when uncertainty clouds the process of decision-making about a choice among multiple alternatives, fuzzy sets are utilized (Govindan et al., 2017). Hence, in this study, Pythagorean fuzzy sets are applied to deal with ambiguity in input data. Fuzzy sets, which were first introduced by Zadeh (1965), are appropriate tools to express the uncertain nature of data (Tavakkoli-Moghaddam et al., 2009) such that can bring about a reduction in imprecise forecasting. After, Atanassov (1986) developed intuitionistic fuzzy sets as an extended version of traditional fuzzy sets to deal with ambiguous data. Since intuitionistic fuzzy sets' inability to capture conditions for degrees of membership and non-membership greater than 1 has always been a problem in many fields, thus, Yager (2014) presented Pythagorean fuzzy sets to bridge this gap. Recently, Yu et al. (2019) and Yazdi

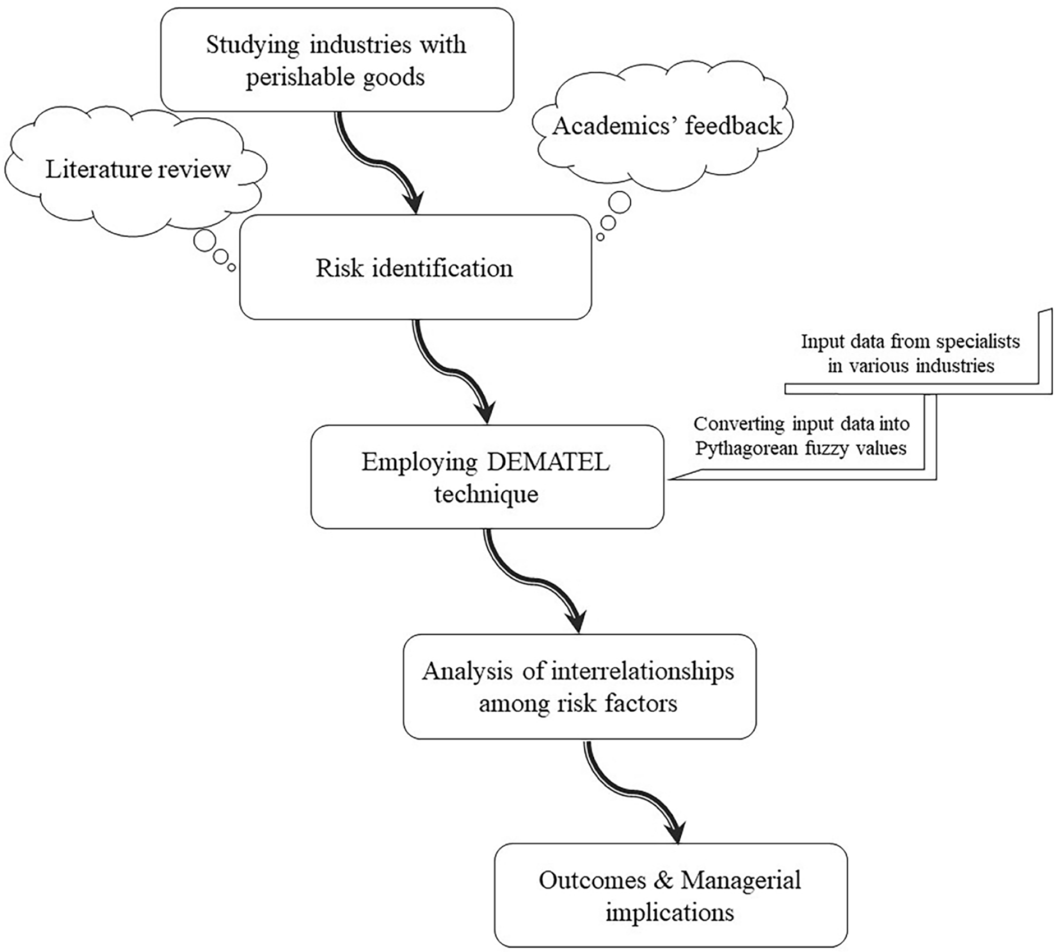

Fig. 2. Study framework.

et al. (2020) claimed that Pythagorean fuzzy sets cope better with the ambiguity of the expert-elicitation approaches.

Suppose that X is a universe of discourse. Then, a Pythagorean fuzzy set P is an object as follows:

$$P = \{ \langle x, \ P(\mu_P(x), \ v_P(x)) \rangle | x \in X \} \tag{1}$$

where $\mu_P(x) : X \to [0, \ 1]$ denotes the degree of membership of the $x \in X$ to P. In addition, $v_P(x) : X \to [0, \ 1]$ indicates the degree of non-membership of the $x \in X$ to P. Plus, for every single$x \in X$, Eq. (2) holds as follows:

$$0 \leqslant \mu_P(x)^2 + v_P(x)^2 \leqslant 1 \tag{2}$$

For every Pythagorean fuzzy set, P and$x \in X$, the degree of indeterminacy of x to P is denoted by$\pi_P(x) = \sqrt{1 - \mu_P(x)^2 - v_P(x)^2}$. To sum up, $\beta = P(\mu_P(x), \ v_P(x))$ is a Pythagorean fuzzy number in a manner that the values of μ_P and v_P lie between 0 and 1, and$\mu_P^2 + v_P^2 \leqslant 1$. Also, further information about basic operations on Pythagorean fuzzy numbers can be found in the studies by Zhang (2016), Cui et al. (2018), Abdullah and Goh (2019), and Yazdi et al. (2020).

3.2. An extended DEMATEL technique

Since the extended version of the DEMATEL method uses Pythagorean fuzzy sets, a few changes have been made compared to the conventional DEMATEL method. The implementation procedure of the extended DEMATEL technique is summarized in the following steps.

Step 1: Determination of linguistic variables.

The initial step to perform the DEMATEL technique is to define the linguistic variables. In this study, experts applied the linguistic terms shown in Table 3 to express the cause-and-effect relations among risk factors.

Step 2: Creating the direct-relation matrix.

The second step is to create a $n \times 2n$ direct-relation matrix, as shown in Eq. (3). An incongruous group of specialists in various perishable product industries were inquired to evaluate the interrelationships amid risk factors. Then, each expert evaluated the cause-and-effect relations among risk factors using linguistic terms in Table 3. Let $\widetilde{r}_{ij} = \left(\mu_{ij}, \ v_{ij}\right)$ be an entry from the direct-relation matrix, where $\mu_{ij} \in [0, \ 1]$ and$v_{ij} \in [0, \ 1]$. As mentioned previously, μ_{ij} and v_{ij} indicate the membership degree and the non-membership degree of the entry in the i^{th} row and j^{th} column.

$$\widetilde{M} = \left[\widetilde{r}_{ij}\right]_{n \times 2n} = \begin{bmatrix} (0, \ 0) & (\mu_{12}, \ v_{12}) & \cdots & (\mu_{1n}, \ v_{1n}) \\ (\mu_{21}, \ v_{21}) & (0, \ 0) & \cdots & (\mu_{2n}, \ v_{2n}) \\ \vdots & \vdots & \vdots & \vdots \\ (\mu_{n1}, \ v_{n1}) & (\mu_{n2}, \ v_{n2}) & \cdots & (0, \ 0) \end{bmatrix}, \ i, \ j \in \{1, 2, ..., n\} \tag{3}$$

Step 3: Aggregation of experts' opinions.

After experts complete the direct-relation matrix, the resulting matrices are aggregated into a single matrix. Thus, the mean Pythagorean fuzzy decision matrix is calculated using Eq. (4), where, k denotes each expert's judgment and$k = 1, \ 2, \ \dots, m$.

$$\widetilde{\overline{M}} = \left[\widetilde{a}_{ij}\right]_{n \times 2n} = \left[\left(\sqrt{1 - \prod_{k=1}^{m}\left(1 - (\mu_{ij})^2\right)^{\frac{1}{m}}}, \ \prod_{k=1}^{m}(v_{ij})^{\frac{1}{m}}\right)\right]_{n \times n} \tag{4}$$

Step 4: Defuzzification.

Concerning that numbers are in Pythagorean fuzzy form, the defuzzification process is done via Eq. (5), resulting in the mean crisp matrix. In Eq. (5), φ denotes risk preference coefficient, which lies between 0 and 1. In fact, φ is the importance of indeterminacy degree (Yazdi et al., 2020).

$$Cr_{\alpha_{ij}} = 0.5\left(1 + \mu_{ij} - v_{ij} + (\varphi - 0.5) \times \pi_{ij}\right) \tag{5}$$

Thus, the mean crisp matrix is converted, as in Eq. (6).

Table 3
Linguistic terms and Pythagorean fuzzy numbers for evaluating interrelations among risks (Cui et al., 2018; Yazdi et al., 2020).

Linguistic terms	Pythagorean fuzzy sets
Very low influence (VLI)	(0.15, 0.85)
Low influence (LI)	(0.25, 0.75)
Moderately low influence (MLI)	(0.35, 0.65)
Medium influence (MI)	(0.50, 0.45)
Moderately high influence (MHI)	(0.65, 0.35)
High influence (HI)	(0.75, 0.25)
Very high influence (VHI)	(0.85, 0.15)

$$C = \left[Cr_{\alpha_{ij}}\right]_{n\times n} \tag{6}$$

Step 5: Normalization of the mean crisp matrix.

The next step is to create the normalized mean crisp matrix N. The normalized mean crisp matrix is computed using Eq. (7). It should be mentioned that $\sum_{j=1}^{n} Cr_{\alpha_{ij}}$ is the summation of each row.

$$N = \frac{1}{\max\sum_{j=1}^{n} Cr_{\alpha_{ij}}} \times C,\ i \in \{1,2,...,n\} \tag{7}$$

Step 6: Creating the total-relation matrix.

Assume that the matrix of I indicates the unit matrix. Multiplying the normalized mean crisp matrix N by the inverse of $(I-N)$ brings about the total relation matrix, as shown in Eq. (8). The total relation matrix shows the entire direct and indirect causal relations among risks.

$$T = N(I-N)^{-1} = \left[t_{ij}\right]_{n\times n},\ i,\ j \in \{1,2,...,n\} \tag{8}$$

Step 7: Acquiring causal diagram.

Obtaining causal diagram is the last step of Pythagorean fuzzy DEMATEL technique. To that aim, the aggregation of rows (D) and the aggregation of columns (R) are computed, as indicated in Eqs. (9) and (10).

$$D_i = \sum_{i=1}^{n} t_{ij} \tag{9}$$

$$R_j = \sum_{j=1}^{n} t_{ij} \tag{10}$$

Eventually, the causal diagram is acquired by graphing the dataset of$(D_i + R_j,\ \ D_i - R_j)$. Where the horizontal axis of $(D_i + R_j)$ demonstrates the importance of criteria and the vertical axis of $(D_i - R_j)$ indicates the degree of relation. Given that the sum of rows (D_i) and the sum of columns (R_j) are given impact and received impact, respectively, the value $(D_i + R_j)$ indicates the total prominence of the impact of each factor (Jeng, 2015; Yazdi et al., 2020). Whenever$(D_i - R_j)$>0, the i^{th} criterion is effective, which will be displayed in the cause category. However, on the other hand, when $(D_i - R_j)$ is negative, the i^{th} criterion is susceptive so that it will be depicted in the effect category.

4. Case study and results

In this section, a real-life case study and its results are provided.

4.1. Case study

The share of perishable goods has been climbed since consumers have shown a propensity to purchase high-quality, fresh, and safe products (Deng et al., 2019). Almost more than 15% of Iran's GDP is constituted by agriculture, foodstuff, beverage, and pharmaceutical industries (Agri-food & Packaging, 2016; Assolombarda, 2020; Statista, 2021). Plus, the mentioned industries have a significant share of Iran's total export, which reflects the importance of Iran's perishable product industries to neighboring countries. Generally speaking, PPSCNs have to deal with various issues, including low logistics efficiency, uncertain nature of events related to

Table 4
Complementary details on participants.

No.	Type of supply chain network	Entity type	Location	Company name	Position of experts
1	Pharmaceutical supply chain network	Distributor	Ilam	Yara Teb Samen Co.	Manager
2	Pharmaceutical supply chain network	Manufacturer	Alborz	Soha Pharma Co.	Production manager
3	Beverage supply chain network	Manufacturer	Ilam	Kooshab Gharb Ilam Co.	Manager
4	Beverage supply chain network	Manufacturer	Ilam	Kooshab Gharb Ilam Co.	Sales manager
5	Beverage supply chain network	Manufacturer	Ilam	Kooshab Gharb Ilam Co.	Production manager
6	Beverage supply chain network	Manufacturer	Ilam	Kooshab Gharb Ilam Co.	Administrative manager
7	Agri-food supply chain network	Manufacturer	Kermanshah	Rojin Taak Co.	Planning manager
8	Agri-food supply chain network	Manufacturer	Kermanshah	Rojin Taak Co.	Production planning expert
9	Agri-food supply chain network	Manufacturer	Kermanshah	Rojin Taak Co.	Production planning expert
10	Agri-food supply chain network	Manufacturer	Kermanshah	Rojin Taak Co.	System and strategy expert
11	Dairy supply chain network	Manufacturer	Tehran	Pajan dairy Co.	Lab manager
12	Dairy supply chain network	Manufacturer	Tehran	Pajan dairy Co.	Production manager
13	Dairy supply chain network	Manufacturer	Tehran	Pajan dairy Co.	Quality control manager
14	Dairy supply chain network	Manufacturer	Tehran	Pajan dairy Co.	Production manager of liquid dairy
15	Dairy supply chain network	Manufacturer	Semnan	Siberia Co.	Quality control manager

Table 5
The total-relation matrix.

	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15
R1	0.0428	0.0101	0.0050	0.0081	0.0088	0.0065	0.0069	0.0082	0.0084	0.0051	0.0075	0.0061	0.0092	0.0070	0.0057
R2	0.0090	0.0428	0.0100	0.0098	0.0086	0.0085	0.0066	0.0082	0.0045	0.0054	0.0071	0.0081	0.0078	0.0057	0.0041
R3	0.0061	0.0104	0.0416	0.0079	0.0080	0.0060	0.0043	0.0052	0.0036	0.0047	0.0056	0.0067	0.0065	0.0052	0.0037
R4	0.0108	0.0120	0.0099	0.0429	0.0094	0.0090	0.0057	0.0066	0.0049	0.0052	0.0093	0.0089	0.0099	0.0077	0.0051
R5	0.0111	0.0106	0.0094	0.0109	0.0432	0.0109	0.0062	0.0071	0.0075	0.0070	0.0079	0.0090	0.0092	0.0068	0.0067
R6	0.0064	0.0106	0.0088	0.0099	0.0096	0.0418	0.0046	0.0053	0.0065	0.0057	0.0064	0.0064	0.0075	0.0057	0.0051
R7	0.0060	0.0059	0.0060	0.0069	0.0069	0.0058	0.0413	0.0069	0.0070	0.0066	0.0050	0.0049	0.0077	0.0061	0.0049
R8	0.0097	0.0089	0.0068	0.0080	0.0062	0.0053	0.0055	0.0417	0.0095	0.0046	0.0053	0.0063	0.0079	0.0068	0.0071
R9	0.0070	0.0059	0.0046	0.0055	0.0067	0.0060	0.0060	0.0071	0.0411	0.0058	0.0045	0.0055	0.0055	0.0058	0.0058
R10	0.0071	0.0079	0.0064	0.0056	0.0074	0.0070	0.0071	0.0044	0.0071	0.0412	0.0065	0.0054	0.0070	0.0060	0.0053
R11	0.0082	0.0099	0.0088	0.0105	0.0096	0.0081	0.0077	0.0066	0.0059	0.0069	0.0428	0.0071	0.0100	0.0088	0.0068
R12	0.0093	0.0069	0.0066	0.0094	0.0097	0.0080	0.0046	0.0049	0.0044	0.0052	0.0103	0.0424	0.0092	0.0072	0.0066
R13	0.0106	0.0082	0.0075	0.0088	0.0110	0.0098	0.0081	0.0054	0.0066	0.0083	0.0113	0.0101	0.0433	0.0080	0.0070
R14	0.0071	0.0078	0.0084	0.0093	0.0082	0.0075	0.0070	0.0053	0.0065	0.0058	0.0094	0.0072	0.0092	0.0421	0.0057
R15	0.0067	0.0069	0.0053	0.0087	0.0064	0.0072	0.0057	0.0055	0.0064	0.0043	0.0069	0.0074	0.0070	0.0076	0.0412
R16	0.0075	0.0067	0.0070	0.0075	0.0095	0.0077	0.0063	0.0055	0.0083	0.0042	0.0085	0.0091	0.0094	0.0073	0.0068
R17	0.0089	0.0088	0.0068	0.0091	0.0092	0.0076	0.0071	0.0062	0.0057	0.0064	0.0085	0.0092	0.0096	0.0070	0.0060
R18	0.0099	0.0102	0.0082	0.0102	0.0110	0.0096	0.0087	0.0073	0.0092	0.0069	0.0106	0.0098	0.0112	0.0080	0.0054
R19	0.0096	0.0081	0.0080	0.0070	0.0059	0.0053	0.0085	0.0089	0.0069	0.0066	0.0086	0.0083	0.0098	0.0063	0.0055
R20	0.0086	0.0085	0.0061	0.0070	0.0098	0.0064	0.0058	0.0050	0.0060	0.0060	0.0083	0.0073	0.0092	0.0080	0.0066
R21	0.0099	0.0094	0.0072	0.0057	0.0065	0.0043	0.0050	0.0082	0.0060	0.0052	0.0072	0.0068	0.0070	0.0055	0.0051
R22	0.0086	0.0100	0.0069	0.0093	0.0087	0.0065	0.0057	0.0068	0.0046	0.0048	0.0086	0.0064	0.0077	0.0056	0.0056
R23	0.0050	0.0069	0.0068	0.0068	0.0069	0.0051	0.0060	0.0050	0.0044	0.0061	0.0071	0.0059	0.0066	0.0057	0.0050
R24	0.0061	0.0068	0.0038	0.0046	0.0056	0.0054	0.0042	0.0044	0.0048	0.0052	0.0052	0.0054	0.0070	0.0056	0.0041
R25	0.0077	0.0080	0.0060	0.0057	0.0081	0.0056	0.0057	0.0047	0.0047	0.0064	0.0077	0.0091	0.0092	0.0089	0.0054
R26	0.0052	0.0065	0.0054	0.0045	0.0036	0.0053	0.0072	0.0033	0.0055	0.0044	0.0044	0.0054	0.0057	0.0039	0.0036
R27	0.0054	0.0071	0.0046	0.0049	0.0062	0.0051	0.0062	0.0033	0.0041	0.0057	0.0041	0.0040	0.0049	0.0033	0.0038
R28	0.0095	0.0063	0.0042	0.0058	0.0061	0.0052	0.0045	0.0092	0.0067	0.0045	0.0074	0.0078	0.0057	0.0031	0.0042
R29	0.0052	0.0074	0.0055	0.0044	0.0052	0.0034	0.0062	0.0048	0.0049	0.0030	0.0048	0.0045	0.0050	0.0035	0.0035

PPSCNs, long transportation time, and immense product losses (Yan, 2017; Xu et al., 2020). Moreover, COVID-19 has adversely influenced all sectors of supply chain networks. Given that PPSCNs provide essential products for a living, undoubtedly, they have to deal with a more sophisticated situation during the COVID-19 pandemic. Since perishable products constitute a significant part of the GDP in every country, the GDP of many countries has experienced a serious decline during the COVID-19 outbreak era, i.e., Germany's GDP reduced by 6% in 2020 compared to 2019 (Burgos and Ivanov, 2021). Similarly, statistical evidence suggests that the COVID-19 has negatively impacted the GDP of India, France, China, Singapore, etc. (Jeudy, 2021; Mangla, 2021; Shaikh et al., 2021). Therefore, in this study, we focused on studying risks to perishable product industries during a pandemic. To that aim, we inquired experts in perishable product industries to provide input data in order to analyze interrelations among risk factors to PPSCNs during the COVID-19 outbreak era. To that aim, experts were asked to determine interrelations among the identified risks in Table 1 using the linguistic terms shown in Table 3.

To make this study more valid and reliable, we established communication with companies in five different Iran provinces. Experts in various PPSCNs, including pharmaceutical, beverage, agri-food, and dairy companies, were inquired to provide input data on interrelations among risks to perishable product industries. In the data collection process, we explained our problem in detail to the managers of Yara Teb Samen, Soha Pharma, Kooshab Gharb Ilam, Rojin Taak, Pajan dairy, and Siberia companies. We asked for volunteer managers and experts to participate in determining interrelations among risks to PPSCNs during the COVID-19 pandemic. The data collection process included various stages, i.e., establishing communication with companies, holding online meetings, and describing the problem to the managers. For the sake of clarification, the third stage of the data collection process is expressed. First, each company introduced some managers and experts as participants to provide input data. Posterior to that, the third stage of the data collection process began. In this stage, the problem was well-described to the participants. Moreover, we clarified the concept of each identified risk so that the participants could determine interrelations among the identified risks in full awareness. So, participants were given an empty matrix, wherein columns and rows of the matrix consisted of the identified risks in Table 1. Participants were told that the effect of each identified risk on itself is equal to zero. So, the final matrix filled by each participant would be a matrix with the main diagonal equal to zero. Next, participants were asked to determine the effect of each identified risk (each row) on all identified risks (columns) using the linguistic terms shown in Table 3. During the process, participants' questions were answered to resolve the ambiguity. Likewise, participants filled the matrix row by row. Lastly, to finalize the direct-relation matrix, we converted the input data provided by participants to Pythagorean fuzzy numbers. It should be mentioned that the entire data collection process took almost one month. Table 4 reports information about participants who provided input data.

4.2. Results analysis

We used the 2016 version of the Excel software to obtain the total-relation matrix, as reported in Table 5. Afterward, using Eqs. (9)

R16	R17	R18	R19	R20	R21	R22	R23	R24	R25	R26	R27	R28	R29
0.0053	0.0071	0.0086	0.0092	0.0074	0.0090	0.0084	0.0052	0.0068	0.0062	0.0075	0.0059	0.0086	0.0068
0.0061	0.0066	0.0064	0.0054	0.0059	0.0060	0.0092	0.0053	0.0056	0.0070	0.0070	0.0059	0.0073	0.0067
0.0072	0.0065	0.0065	0.0057	0.0061	0.0067	0.0053	0.0047	0.0059	0.0075	0.0046	0.0051	0.0045	0.0059
0.0081	0.0085	0.0088	0.0056	0.0088	0.0077	0.0088	0.0060	0.0069	0.0077	0.0073	0.0070	0.0076	0.0087
0.0069	0.0079	0.0075	0.0058	0.0082	0.0077	0.0095	0.0086	0.0066	0.0080	0.0080	0.0096	0.0091	0.0066
0.0060	0.0061	0.0062	0.0053	0.0062	0.0065	0.0073	0.0075	0.0050	0.0061	0.0053	0.0070	0.0043	0.0047
0.0063	0.0050	0.0052	0.0068	0.0048	0.0063	0.0066	0.0053	0.0049	0.0057	0.0069	0.0069	0.0050	0.0058
0.0073	0.0071	0.0069	0.0083	0.0071	0.0096	0.0087	0.0072	0.0063	0.0061	0.0064	0.0045	0.0074	0.0056
0.0060	0.0053	0.0053	0.0046	0.0051	0.0051	0.0062	0.0048	0.0050	0.0055	0.0055	0.0061	0.0068	0.0043
0.0053	0.0075	0.0067	0.0061	0.0074	0.0066	0.0066	0.0072	0.0051	0.0055	0.0068	0.0093	0.0064	0.0050
0.0074	0.0080	0.0095	0.0071	0.0078	0.0068	0.0084	0.0070	0.0057	0.0087	0.0079	0.0068	0.0087	0.0067
0.0079	0.0076	0.0087	0.0060	0.0075	0.0071	0.0087	0.0072	0.0083	0.0077	0.0065	0.0043	0.0069	0.0055
0.0084	0.0090	0.0083	0.0069	0.0082	0.0066	0.0093	0.0081	0.0074	0.0094	0.0091	0.0082	0.0064	0.0065
0.0084	0.0081	0.0092	0.0056	0.0093	0.0067	0.0075	0.0075	0.0076	0.0082	0.0072	0.0073	0.0065	0.0069
0.0068	0.0069	0.0094	0.0053	0.0078	0.0059	0.0065	0.0074	0.0068	0.0071	0.0064	0.0066	0.0056	0.0061
0.0420	0.0082	0.0095	0.0064	0.0079	0.0064	0.0068	0.0071	0.0078	0.0090	0.0065	0.0072	0.0069	0.0065
0.0063	0.0426	0.0103	0.0065	0.0084	0.0081	0.0085	0.0089	0.0078	0.0101	0.0079	0.0088	0.0082	0.0073
0.0082	0.0101	0.0433	0.0075	0.0106	0.0090	0.0100	0.0100	0.0092	0.0096	0.0087	0.0090	0.0092	0.0068
0.0061	0.0078	0.0085	0.0421	0.0072	0.0069	0.0105	0.0087	0.0061	0.0088	0.0095	0.0065	0.0096	0.0057
0.0066	0.0062	0.0090	0.0079	0.0423	0.0074	0.0067	0.0086	0.0083	0.0087	0.0104	0.0083	0.0078	0.0059
0.0063	0.0067	0.0058	0.0070	0.0068	0.0421	0.0099	0.0071	0.0064	0.0052	0.0070	0.0070	0.0081	0.0060
0.0060	0.0066	0.0073	0.0062	0.0048	0.0086	0.0424	0.0056	0.0043	0.0061	0.0068	0.0066	0.0079	0.0045
0.0048	0.0060	0.0060	0.0060	0.0057	0.0070	0.0088	0.0417	0.0057	0.0061	0.0076	0.0065	0.0054	0.0057
0.0046	0.0049	0.0071	0.0054	0.0062	0.0068	0.0067	0.0063	0.0412	0.0079	0.0075	0.0055	0.0050	0.0056
0.0051	0.0080	0.0095	0.0060	0.0076	0.0086	0.0091	0.0073	0.0094	0.0423	0.0086	0.0068	0.0058	0.0077
0.0051	0.0041	0.0053	0.0040	0.0047	0.0059	0.0063	0.0076	0.0047	0.0047	0.0413	0.0054	0.0052	0.0081
0.0038	0.0040	0.0035	0.0038	0.0030	0.0043	0.0044	0.0054	0.0033	0.0045	0.0043	0.0407	0.0035	0.0039
0.0046	0.0067	0.0061	0.0071	0.0062	0.0077	0.0075	0.0048	0.0058	0.0054	0.0062	0.0049	0.0416	0.0036
0.0031	0.0050	0.0047	0.0036	0.0042	0.0063	0.0054	0.0061	0.0047	0.0061	0.0081	0.0041	0.0047	0.0407

and (10), the values of $(D_i + R_j)$ and $(D_i - R_j)$ were obtained, as shown in Table 6. As a complementary component to Table 5, the casual diagram is depicted in Fig. 3.

A wide range of remarkable results was gained analyzing the causal diagram. Results of the analysis indicated that competitive risks (R27), changes in consumer tastes (R26), political instability (R2), market share reduction (R29), lean inventory (R22), war threats (R3), warehouse disruption (R23), distribution network breakdown (R28), labor shortage because of being infected with COVID-19 (R24), new restrictions because of the COVID-19 outbreak (R1), IT failures (R9), machine breakdown (R21), seasonal variations (R6), and transportation incidents (R7) were classified into the effect category, respectively. The effect category can easily be affected by other risks since their $(D_i - R_j)$ is negative. Plus, perishability period of products (R18), unhealthy working environment (R19), single supply sourcing (R15), supplier bankruptcy (R14), delay in delivery of raw material (R16), work-hour (R17), inadequate road infrastructure (R8), power outage (R10), labor strike (R20), currency volatility (R11), increase in COVID-19 cases (R5), fuel price fluctuations (R13), natural disasters (R4), increase in freight charges (R12), and demand uncertainty (R25) turned out to be influential risks, respectively, because of the fact that their $(D_i - R_j)$ is positive. Thus, the cause category can profoundly impact the effect category.

As formerly mentioned, once $(D_i + R_j)$ increases, the importance of relative risk rises. The analysis revealed that perishability period of products (R18), fuel price fluctuations (R13), and increase in COVID-19 cases (R5) have the highest $(D_i + R_j)$ scores, respectively. In other words, during the pandemic outbreak era, perishability period of products (R18), fuel price fluctuations (R13), and increase in COVID-19 cases (R5) have significant impacts on most of the other risks to PPSCNs. Moreover, in $(D_i + R_j)$ ranking, as infrastructural risks, transportation incidents (R7), inadequate road infrastructure (R8), IT failures (R9), and power outage (R10) have scores of 0.42417, 0.44911, 0.41021, and 0.42007, respectively. On the other hand, currency volatility (R11), increase in freight charges (R12), and fuel price fluctuations (R13) have higher $(D_i + R_j)$ scores. Altogether, this outcome indicates that infrastructural risks have lesser criticality during the pandemic outbreak, except for financial and energy risks.

According to results, perishability period of products (R18), unhealthy working environment (R19), single supply sourcing (R15), supplier bankruptcy (R14), delay in delivery of raw material (R16), and work-hour (R17) are highly influential in such a way that they can foment most of the other risks. The analysis revealed a clear and lucid consensus among experts that the perishability period of products (R18) is the most influential risk factor, especially during the pandemic outbreak era. Thus, meticulous planning decisions are required to forestall the side-effects of the COVID-19 spread on PPSCNs. Furthermore, according to the Table 6, an unhealthy working environment (R19) with the $(D_i - R_j)$ score of 0.04418 is the second influential risk factor. Besides, three supply-side risks, including single supply sourcing (R15), supplier bankruptcy (R14), and delay in delivery of raw material (R16), turned out to be significant risk factors, even during the COVID-19 outbreak era. Moreover, results revealed that work-hour (R17) has emerged as one of the influential risk factors during the COVID-19 outbreak era.

Additionally, results indicated a consensus among experts that competitive risks (R27), changes in consumer tastes (R26), political instability (R2), market share reduction (R29), and lean inventory (R22) are the most susceptive risk factors in such a way that they can easily be influenced by other risk factors. In $(D_i - R_j)$ ranking, competitive risks (R27) have the lowest value among all effects. As a matter of fact, this issue shows that experts reckon that the competition among PPSCNs has become fiercer after the advent of COVID-19 infection. Results demonstrated that an increase in COVID-19 cases (R5) and the perishability period of products (R18) leave the most effects on competitive risks, respectively. After competitive risks (R27), changes in consumer tastes (R26) and political instability (R2) turned out to be the most susceptive risk factors. Plus, according to Table 6, market share reduction (R29) is the fourth susceptive risk factor with a $(D_i - R_j)$ score of -0.03189. Results indicated that natural disasters (R4) and changes in consumer tastes (R26) are the most influential risks that can cause a reduction in market share. Moreover, another finding of this study is that experts believed that lean inventory (R22) is a susceptive risk factor to PPSCNs during the COVID-19 outbreak era.

5. Discussion

In this section, we validate our findings using the literature in the PPSCN context, supply chain network context, and recently published articles about the effects of the COVID-19 on businesses.

The analyses revealed that the perishability period of products (R18) leaves serious effects on most of the other identified risk factors. Perishable products can easily be influenced by environmental factors and get deteriorated during the flow and transportation process of the supply chain (Liu et al., 2018). During the peak days of COVID-19, many governments try to contain the outbreak by increasing rigorous lockdowns. Undoubtedly, lockdowns exacerbate this issue. Moreover, a recent study by Mahajan and Tomar (2021) clearly indicates that lockdowns can pose a threat to food supply chain networks from several perspectives. Consequently, during the pandemic outbreak, the perishability period of products easily affects the effect category factors. Additionally, it turned out that an unhealthy working environment (R19) is the second influential factor. As shown in Table 5, an unhealthy working environment (R19) profoundly influences changes in consumer tastes (R26). By the same token, Apple Inc. received negative backlash in China due to an inappropriate working environment; consequently, the sale of Apple's products dramatically fell in China (Hofmann et al., 2014). Furthermore, supply-side risks have always been problematic for supply chain networks. Our findings strongly suggest that single supply sourcing (R15), supplier bankruptcy (R14), and delay in delivery of raw material (R16) are still the most influential risks to PPSCNs. As can be witnessed in Table 5, single supply sourcing (R15), supplier bankruptcy (R14), and delay in delivery of raw material (R16) highly affect the perishability period of products (R18), which doubles the complexity of business continuity during the COVID-19 outbreak era. Mahajan and Tomar (2021) declared that lockdowns directly influence the transportation of products, which brings about the delay in delivery of raw material. Subsequently, this delay impacts the perishability period of products (R18). Above all, work-hour (R17), as a manufacturing risk, has lately emerged as an influential risk factor during the COVID-19 outbreak era for PPSCNs. Results showed that work-hour (R17) could lead to an increase in COVID-19 cases (R5). Similarly, a new study by Ran et al. (2020) discussed that work-hour has an influence on the COVID-19 transmission rate. Also, our findings revealed that new restrictions because of the COVID-19 outbreak (R1) would be imposed due to an increase in COVID-19 cases (R5).

In the recent study by Wan et al. (2019b), the fierce competition turned out to be the most significant risk factor in the context of maritime container supply chains. Similarly, our analyses indicated that PPSCNs are highly prone to competitive risks (R27) during the COVID-19 outbreak era. This finding sounds logical due to the fact that PPSCNs have to deal with the actual risk of COVID-19 alongside former risks. Moreover, results showed that the second susceptive factor in the effect category is changes in consumer tastes (R26), which can easily get impacted by risk factors during the COVID-19 outbreak era. Likewise, recently, Appiah-Nimo and Agyapong (2020) claimed that customers' tastes have been profoundly changed after the advent of COVID-19. Another finding of this study is that political instability (R2) is the third susceptive factor that can easily get influenced by several risk factors in the cause category. According to the results, an increase in COVID-19 cases (R5), as one of the major influential risks in the cause category, can foment political instability (R2). Besides, recently, Rutayisire et al. (2020) argued that the COVID-19 spread could come as a devastating blow to the African continent due to several reasons, such as political instability, which subsequently causes aggravation of the condition. Furthermore, as previously mentioned, analyses indicated a limpid and clear consensus among experts that lean inventory (R22) can be a highly vulnerable factor during the COVID-19 outbreak era. According to the results, in the cause category, an unhealthy working environment (R19), perishability period of products (R18), and an increase in COVID-19 cases (R5) are the most influential risk factors that could be problematic to PPSCNs that use a lean inventory system. Similarly, Berghel et al. (2020) discussed that lean supply chain networks have become more vulnerable during the COVID-19 outbreak era.

6. Implications

In this section, theoretical contributions, managerial contributions, as well as policy contributions are presented.

6.1. *Theoretical contributions*

From the theoretical perspective, this paper contains several theoretical contributions. First of all, a comprehensive classification of supply chain risks is provided. Such a comprehensive classification gives researchers and academics a precise view of risks' origin. So, researchers and academics will reach a sharper understanding of the probable risks to supply chain networks. Second of all, this paper is the first to study interrelations among risks to PPSCNs during the COVID-19 outbreak era employing an extended version of the

Table 6
The values of $(D_i + R_j)$ and $(D_i - R_j)$ vectors.

Risks		$(D_i + R_j)$	$(D_i - R_j)$	Nature
R18	Perishability period of products	0.54662	0.04821	Cause
R19	Unhealthy working environment	0.47047	0.04418	
R15	Single supply sourcing	0.41901	0.03658	
R14	Supplier bankruptcy	0.47055	0.03476	
R16	Delay in delivery of raw material	0.46540	0.03311	
R17	Work-hour	0.50008	0.03157	
R8	Inadequate road infrastructure	0.44911	0.02663	
R10	Power outage	0.42007	0.02555	
R20	Labor strike	0.48568	0.01938	
R11	Currency volatility	0.51110	0.01745	
R5	Increase in COVID-19 cases	0.53571	0.01162	
R13	Fuel price fluctuations	0.54034	0.01090	
R4	Natural disasters	0.51967	0.00996	
R12	Increase in freight charges	0.48521	0.00402	
R25	Demand uncertainty	0.48514	0.00383	
R7	Transportation incidents	0.42417	−0.00535	Effect
R6	Seasonal variations	0.45358	−0.00638	
R21	Machine breakdown	0.46961	−0.00885	
R9	IT failures	0.41021	−0.01306	
R1	New restrictions because of the COVID-19 outbreak	0.51250	−0.01766	
R24	Labor shortages because of being infected with COVID-19	0.41746	−0.01963	
R28	Distribution network breakdown	0.43851	−0.02134	
R23	Warehouse disruption	0.44648	−0.02219	
R3	War threats	0.43906	−0.02399	
R22	Lean inventory	0.48964	−0.03035	
R29	Market share reduction	0.38772	−0.03189	
R2	Political instability	0.51193	−0.03825	
R26	Changes in consumer tastes	0.42897	−0.05611	
R27	Competitive risks	0.39290	−0.06269	

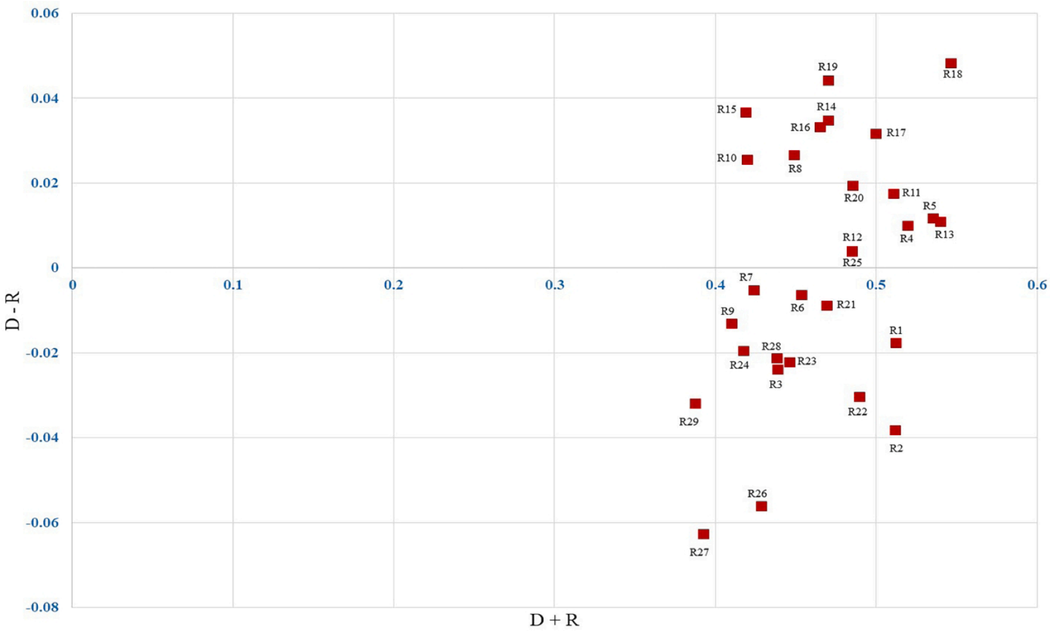

Fig. 3. Casual diagram.

DEMATEL method. Previous studies have neglected several risks that may arise during a crisis. Hence, a causality analysis of risks to PPSCNs during a crisis bridges the gap in the literature. Furthermore, the DEMATEL method is a felicitous tool for researchers and scholars in order to investigate the interrelations among various factors, i.e., risks, etc. Lastly, we inquired experts from various perishable product industries to provide data, which required a proper manner to deal with the ambiguity of input data. As a matter of fact, coping with the ambiguity of input data is one of the main steps in expert-elicitation approaches. Thus, using a proper ambiguityhandling method, researchers can reach more reliable outcomes. In line with what was discussed, Pythagorean fuzzy sets were utilized to handle the ambiguity of experts' opinions. Pythagorean fuzzy numbers are newly invented fuzzy numbers, which can effectively deal with the vagueness of data (Yu et al., 2019; Yazdi et al., 2020).

6.2. Managerial contributions

Supply chain networks are the economic artery of countries in such a way that they have a vital role in the financial state of societies, as well as social and environmental conditions. Overlooking risk assessment, companies may encounter many risks, particularly during the COVID-19 outbreak era. Consequently, they cannot obviate the need for products during the COVID-19 pandemic. As the first stride in coping with the destructive effects of the pandemic outbreaks on business, risk assessment is a felicitous guide to help firms keep their businesses afloat. As a matter of fact, the aim of risk assessment is to make preparation for the subsequent risk management practices, including decreasing and control of risks (El-Baz and Ruel, 2021). This paper aims at analyzing the interrelations among risks to PPSCNs during the COVID-19 outbreak era. So, the outcome of this study can act as a comprehensive guideline for managers. Thus, managers of supply chain networks can divide their capital commensurate with the impact and importance of risks. Hence, managers can decide with an informed background by implementing such an approach. The extracted managerial insights of this study for managers and decision-makers are brought as follows:

(i). As previously mentioned, analyses revealed that the perishability period of products (R18) has the greatest influence on factors in the effect category during the COVID-19 outbreak era. Hence, managers should be aware that the perishable nature of products can easily involve other risks. To cope with the perishability period of products (R18), managers can employ technologies to extend the shelf life of products. For instance, several packaging technologies, including modified atmosphere packaging technology, active packaging, smart packaging, etc., can lengthen product shelf life (Tornuk et al., 2015; Schaefer and Cheung, 2018; Qu et al., 2022). Plus, managers need to allocate more funds to ameliorate working conditions in order to attenuate the knock-on effects of the unhealthy working environment (R19). Furthermore, according to this study's findings, single supply sourcing (R15), supplier bankruptcy (R14), and delay in delivery of raw material (R16), as supply-side risks, are the most influential risk factors after the unhealthy working environment (R19). So, managers should consider proper strategies to cope with supply-side risks during the COVID-19 outbreak era. From the most popular strategies to encounter supply-side risks, multiple-sourcing, making a contract with backup suppliers, etc., can be mentioned. Moreover, our analyses showed substantial impacts of work-hour (R17) on other factors in the effect category. Above all, it turned out work-hour (R17) can bring about an increase in COVID-19 cases (R5), which previously was claimed by Ran et al. (2020). To sum up, work-hour enhancement leads to the COVID-19 spread. On the other hand, the work-hour reduction has adverse effects on the production rate. Therefore, managers should set an appropriate work-hour so that the COVID-19 transmission rate is controlled, and subsequently, the production loss rate is minimized.

(ii). Based on our findings, competition among PPSCNs has become severe after the advent of the COVID-19 pandemic. Furthermore, results revealed that risk factors during the COVID-19 outbreak era could profoundly impact the market share reduction (R29) and changes in consumer tastes (R26). Thus, in order to cope with mentioned problems, managers should present appropriate plans to attract consumers' attention toward their products. To that aim, several activities can be done, including new propaganda, discount, new products, innovative marketing strategies, etc. Besides, outcomes revealed a consensus among experts that lean inventory (R22) is highly vulnerable for PPSCNs during the COVID-19 outbreak era. Thus, managers of PPSCNs should consider other inventory strategies during the pandemic outbreak.

6.3. Policy contributions

Our findings strongly support the fact that policy-makers and governments can play a key role in providing a proper setting for businesses during a pandemic outbreak. Results indicated that political instability (R2) and war threats (R3) are respectively the third and sixth prone risks in a way that can easily be fomented by other risks in the time of the COVID-19 outbreak. Politicians should be aware that a pandemic steers all countries to difficulty and affliction. So, it is highly recommended to show conciliatory remarks to avoid political instability (R2) and war threats (R3) as much as possible during the COVID-19 outbreak era. On the other hand, analyses revealed that new restrictions because of the COVID-19 outbreak (R1) might thoroughly influence political instability (R2). Plus, it turned out that it can lead to currency volatility (R11), fuel price fluctuations (R13), etc. Also, it should be mentioned lockdowns and restrictions adversely affect GDP. On the other hand, many governments, on the advice of health experts, have implemented lockdowns in order to curtail the spread of the COVID-19. So, policy-makers should be aware of this fact and try to make a balance between GDP and lockdown through establishing sanitary protocols.

7. Conclusions and outlooks

It is not concealed to anyone that a particular risk may have an influence on other risks. Thus, constructing a framework to study interrelations among risks can be a way to prevent risks and their side-effects. A review of the PPSCN literature indicates that no previous study has tried to analyze interdependency among risks to PPSCNs. Plus, COVID-19 has emerged as a new threat to humanity and global economy as well. Therefore, studying interrelations among risks has become more and more necessary during the COVID-19 outbreak era.

This paper makes a causality analysis of risks to PPSCNs during the COVID-19 outbreak era. To that end, several risk factors to PPSCNs were identified using academics' feedback. Overall, three geopolitical risks, three environmental risks, seven infrastructural risks, three supply-side risks, eight manufacturing risks, and five demand-side risks were selected to be studied. After, we asked a heterogeneous group of experts in perishable product industries, including pharmaceutical supply chain networks, agri-food supply chain networks, beverage supply chain networks, and dairy supply chain networks, to provide input data. Then, we used an extended version of the DEMATEL method under Pythagorean fuzzy environment to analyze interrelations among risks. DEMATEL method, as a decision-making tool, creates a structural model consist of cause-and-effect relationships among factors. Plus, experts' judgments are subject to ambiguity. Thus, we applied Pythagorean fuzzy numbers to cope with vague input data. Results indicated that fifteen risks, including perishability period of products, unhealthy working environment, single supply sourcing, supplier bankruptcy, delay in delivery of raw material, work-hour, inadequate road infrastructure, power outage, labor strike, currency volatility, increase in COVID-19 cases, fuel price fluctuations, natural disasters, increase in freight charges, and demand uncertainty, are categorized into the cause group, respectively. Our findings revealed an apparent consensus among experts that the perishability period of products is the most influential risk such that can easily affect other risks. Plus, outcomes showed that unhealthy working environment with $\left(D_i - R_j\right)$ score of 0.04418 is the second influential risk in the cause group. Additionally, according to results, three supply-side risks, i.e., single supply sourcing, supplier bankruptcy, and delay in delivery of raw material, are influential risks to PPSCNs during the COVID-19 outbreak era. Above all, it turned out that work-hour can be highly influential on a wide range of risks during the COVID-19 outbreak era. On the other hand, results demonstrated that fourteen risks, including competitive risks, changes in consumer tastes, political instability, market share reduction, lean inventory, war threats, warehouse disruption, distribution network breakdown, labor shortage because of being infected with COVID-19, new restrictions because of the COVID-19 outbreak, IT failures, machine breakdown, seasonal variations, and transportation incidents, are categorized into the effect group, respectively. Outcomes revealed that competitive risks are the most susceptive risks. In other words, competition among PPSCNs has become fiercer after the advent of the COVID-19 in Wuhan. Also, we figured out that changes in consumer taste are highly prone to be influenced by other risks easily. Moreover, political instability turned out to be the third susceptive risk among all in the effect group with $\left(D_i - R_j\right)$ score of -0.03825. Plus, results indicated that perishable product market share reduction is also highly prone to be impacted by other risks during the COVID-19 outbreak era. Furthermore, outcomes revealed a clear consensus among experts that a lean inventory system can easily be affected by various risks during the COVID-19 outbreak era.

Similar to other studies, this study has some limitations, which can be an incentive for further studies. Future studies can investigate the interrelations among risks to other industries, such as recyclable product industries. Also, investigating the effects of this study's most critical risks on PPSCNs using mathematical modeling can be a new direction for further studies. Moreover, several risks have been neglected in this study, which can be studied in the future. Lately, a new version of fuzzy sets, namely interval-valued Pythagorean fuzzy sets introduced by Peng and Yang (2016), has received remarkable attention from researchers and scholars. So, studying interrelations among risks to PPSCNs under interval-valued Pythagorean fuzzy environments can be considered a new direction for future works. Furthermore, the last step of risk management is to provide an appropriate response to a particular risk base on analysis. So, new researches can be carried out about how to respond to risks to PPSCNs during the COVID-19 outbreak era based on this study's findings.

CRediT authorship contribution statement

Mohammad Shafiee: Conceptualization, Methodology, Software, Investigation, Writing – original draft, Writing – review & editing. **Yahia Zare-Mehrjerdi:** Conceptualization, Supervision, Writing – review & editing, Project administration. **Kannan Govindan:** Supervision, Writing – review & editing, Validation. **Sohaib Dastgoshade:** Investigation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors appreciate the laudable collaboration of Mr Daraei (manager of Ilam industrial zones), Mr Faramarzi (planning manager of Rojin Taak agro-industries company), Mr Shirazian (production manager of the Soha Pharma company), Mr Siahi (manager of Yara Teb Samen pharmaceutical distributor), Ms Imanzadeh (quality control manager of Pajan dairy company), Ms Alizadeh (quality control manager of Siberia dairy company), and every expert who participated in providing data.

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