



Assessing risk of supply chain disruption due to COVID-19 with fuzzy VIKORSort

Jehangir Khan¹ · Alessio Ishizaka¹  · Sachin Kumar Mangla²

Accepted: 25 August 2022

© The Author(s), under exclusive licence to Springer Science+Business Media, LLC, part of Springer Nature 2022

Abstract

The rapid spread of the COVID-19 pandemic has disrupted many economic activities around the world. The complete and partial lockdown policies, as well as the closure of borders by many countries has halted trade, consequently disrupting domestic and international supply chain networks. Like many other countries, various economic sectors in Pakistan also bore high economic losses due to these disruptions. Multiple studies have analyzed on the impact of the COVID-19 pandemic on different economic sectors in Pakistan, i.e. construction, accommodation and food, manufacturing, wholesale and retail goods, energy, and the information and communication sectors. However, no study has examined sorting these economic sectors based on supply chain disruptions due to the pandemic. Therefore, this study aims to observe the resilience of these economic sectors and perform sorting using three predefined classes, i.e. severe, moderate, and low disruptions. For this purpose, we propose using the novel methodology fuzzy VIKORSort, which is the major contribution of this paper. This methodology evaluates the aforementioned economic sectors based on 10 criteria. The results of the study revealed that the accommodation and food sector, along with the construction sector, experienced the most severe disruption, followed by manufacturing, wholesale and retail goods, and energy, with moderate disruption, whereas the information and communication sector bore the least disruption. The proposed methodology will help the researchers and authorities deal with sorting and decision problems to prioritize the preventive measures of such undesirable events.

Keywords COVID-19 · Supply chain disruptions · Fuzzy VIKORSort · Economic sectors · Pakistan

✉ Alessio Ishizaka
Alessio.ISHIZAKA@neoma-bs.fr

Jehangir Khan
jehangir.khan.20.2@neoma-bs.com

Sachin Kumar Mangla
sachinmangl@gmail.com; smangla@jgu.edu.in

¹ Neoma Business School, 1 rue du Maréchal Juin, BP 215, 76130 Mont-Saint-Aignan Cedex, France

² Director Research Centre On Digital Circular Economy for Sustainable Development Goals (DCE-SDG), Jindal Global Business School, O P Jindal Global University, Sonapat 131001, India

1 Introduction

The advent of the twenty-first century has brought different catastrophic disasters to the face of the earth. Some of the deadliest disasters of the twenty-first century include the 2003 European heatwave, the 2004 Indian Ocean earthquake, the 2005 Kashmir earthquake, the 2008 Nargis Cyclone, 2010 earthquake in Haiti, 2015 earthquake in Nepal, the 2018 Camp Fire in California, and the Australian Bush fires of 2019–2020. All these disasters resulted in millions of human fatalities, along with billions of dollars in economic losses. Currently, the world is facing a new, unprecedented epidemic disaster, a contagious disease called COVID-19, which has disrupted almost every activity around the world (Sarkis et al., 2020). To tackle this pandemic, the World Health Organization (WHO) urged all countries to adopt preventive measures such as avoiding social gatherings, imposing lockdowns, curfews, travel limitations, and restricting economic activities (Anderson et al., 2020).

The novel outbreak produced a sudden shock in the global economy, which disrupted the supply and demand cycles of different economic sectors. For instance, people compulsively bought more essential goods than they needed, disrupting the supply–demand cycle and leading to food shortages and price hikes (Boyaci-Gunduz et al., 2021). For this purpose, a resilient supply chain for the food sector was proposed to tackle the difficulties of varying supply–demand cycles (Singh et al., 2021). The resilience studied is defined as getting the process back to its original state after any distortion due to an undesirable event. The concept of a resilient supply chain has emerged to shield supply chains from swinging from chaotic to tranquil states and to ensure a continuous flow of business operations (Christopher & Peck, 2004). During the COVID-19 pandemic, many countries stopped their regional and foreign trade for fear of spreading COVID-19, exposing the poor resilience and vulnerability of global and regional supply chains (SC) (Obayelu et al., 2020). For example, before the COVID-19 pandemic, China was the major exporter of face masks and medical equipment in the world.¹ However, with the impact on global supply chains and the increase in domestic demand due to COVID-19, China reduced exportation of the required medical equipment, affecting the health sector of many countries, including Pakistan. Moreover, a study in the UK revealed that many construction projects were adversely affected due to the COVID-19 pandemic, with disruption in the supply chain as one of the important causes of Alsharif et al. (1559). Indeed, many European Small- and Medium-sized Enterprises (SMEs) in the manufacturing sector faced serious challenges in smoothly maintaining their supply–demand cycle during the COVID-19 period (Juergensen et al., 2020).

Given this context, it is essential to study the impact on different economic sectors while disruption occurred in the global supply chain due to the COVID-19 pandemic. These disruptions are mainly due to the strict lockdown policies and other preventive measures adopted by many countries, which disturbed logistics activities, custom clearance processes, international shipments, and tracking, etc. (Anser et al., 2021). These preventive measures increased lead-times and transportation costs. The ripple effect of the transportation costs impacted business operation cost, raw material cost, and final product price as well. Therefore, the changes in final product costs and led to fluctuations in product demand. Additionally, the changes in raw material prices and supply–demand cycles fed into the shorter life cycles of different materials, placing suppliers in financial crisis. Although all developed and developing countries suffered serious economic consequences due to the COVID-19 pandemic, it has become a nightmare for a country like Pakistan with an already fragile economic structure prior to the pandemic. In the last two decades, Pakistan experienced economic shrinkage of

¹ <https://www.nytimes.com/2020/03/13/business/masks-china-coronavirus.html>.

around 1.71% due to poor law and order, which proved economically disastrous (Khan et al., 2016). Additionally, there has also been an unusual rise in natural disasters such as floods and earthquakes. According to the Global Climate Risk Index (GCRI) 2021, Pakistan ranks eighth among the countries most vulnerable to climate change (Eckstein et al., 2021).

Given all these of Pakistan's potential hazards and economic conditions, we observed the supply chain resilience of different economic sectors in Pakistan during the COVID-19 pandemic. Based on resilience, we categorized companies into predefined, ordered classes using multi-criteria sorting. These classes will help policymakers develop and prioritize their actions and take proactive or preventive measures in the future against such undesirable events. For this purpose, we identify a set of criteria (potential hazards) and alternatives (economic sectors). We analyze them with a newly developed multi-criteria decision sorting method: fuzzy VIKORSort. The fuzzy set theory in the proposed methodology is a very useful tool for performance assessment (Ammar & Wright, 2000).

The contribution of this research study is multifaceted. Firstly, we propose a novel methodology for sorting based on a fuzzy VIKOR called fuzzy VIKORSort. Secondly, although several studies have been conducted on economic losses due to supply chain disruption because of the COVID-19 pandemic (Chowdhury et al., 2021), not a single study has sorted economic sectors based on these disruptions. Thirdly, unlike other sorting methodologies, this research identifies the limit profiles using a fuzzy set theory, which is an added novelty. The fuzzy limit profiles will provide the basis, i.e. the upper and lower limits for each criterion against the respective economic sector, which then segregates the alternatives into predefined classes. However, one of the shortcomings of the VIKOR method is the rank reversal, where the existing ranking changes with the introduction of new alternatives because of the relative calculation, where the best and worst values fluctuate for each criterion (Ceballos et al., 2018). Therefore, the final contribution of this study towards the scholarly work is to modify the VIKOR method by introducing the ceiling and ground values for each criterion, which remain fixed as the best and worst values respectively and provide an absolute calculation that overcomes the rank reversal problem.

The rest of the article is structured into different sections. Following the first section introducing Supply Chain Management (SCM) and the disruptions due to COVID-19, the second section includes a brief literature review about SCM, different risk factors for supply chains, the disruptions due to the COVID-19 pandemic, the sorting methodologies, and the research gap. The third section presents the new proposed methodology. The fourth section discusses the case study and the details of data collection. The fifth section provides a detailed discussion of the results and managerial implications of this study. Finally, the sixth section presents the conclusion and directions for future research. Figure 1 presents the research flowchart of this study.

2 Literature review

This section provides brief literature on risk and the factors disrupting SCM, the COVID-19 pandemic and disruptions in SCM, sorting based on Multi-Criteria Decision-Making (MCDM), and the research gap for the present study.

2.1 Risk and the factors disrupting SCM

SCM is one of the core business operations that relate to the inflow and outflow of the business processes. An effective SCM ameliorates the brand value of the firm with high

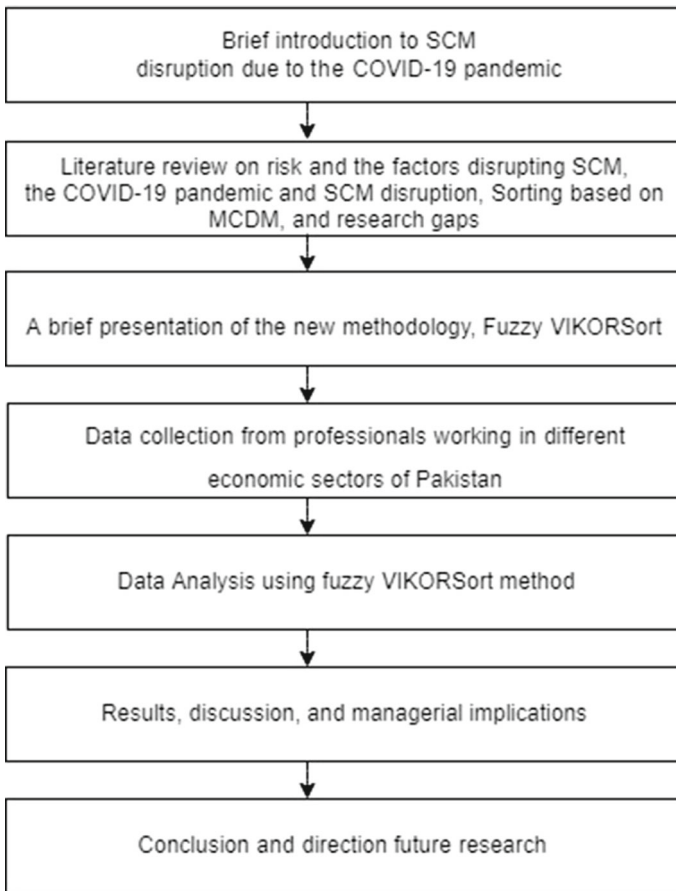


Fig. 1 Research flow chart

customer satisfaction along with a competitive advantage in the marketplace. However, the increase in different uncertain events in the modern world contributes to SCM intricacy, which results in increased exposure to risk, disruption, and vulnerabilities.

Risk in the context of supply chains is defined as anything that hinders or disturbs the continuous flow of information, goods or material from the point of inception to the point of consumption (Christopher et al., 2006). Therefore, supply chain managers must seek insights into the different supply chain risks and should develop proactive contingency plans. Several research studies have explored different risk factors interrupting or disrupting SCM. Disruption in supply chains occur mostly due to natural disasters (earthquakes, floods, etc.) and unlawful activities (Manners-Bell, 2014). For instance, the SCM of manufacturing firms in Japan was heavily affected due to earthquakes, tsunamis, and nuclear disasters. In response, different research studies have been carried out to restore the SCM of Japanese manufacturing firms and develop different contingency plans to minimize the losses of such uncertain events in the future (Park et al., 2013). Furthermore, the 9/11/2001 World Trade Center attack resulted in political instability around the world, which disrupted regional and global SCM (Kleindorfer & Saad, 2005). Similarly, the proliferation of the SCM of electronic media

increased the risk of cyber-attacks, which can seriously disrupt a whole supply chain network (Warren & Hutchinson, 2000a). To deal with such a situation, different studies have sought to highlight different security risks connected with the electronic supply chain (Warren & Hutchinson, 2000b). Likewise, another study was conducted on supply chain disruption using the risk factors of Sovereign risks, manufacturing (processual) breakdowns, demand risks, port delays, and inventory risks (Xie et al., 2011). Sovereign risk is defined as: risk that has evolved due to regional instability, communication difficulties, cultural differences, and government regulations. The cultural differences were one of the important failure factors in maintaining an effective supply chain in the South African flood in 2002 and Hurricane Katrina in 2005 (Dowty & Wallace, 2010). Different studies have examined the risks associated with SCM due to production or manufacturing risks (Shu et al., 2014), material flows from suppliers stored as an inventory, and outbound flows of goods to customers (Habermann et al., 2015). Similarly, threats to the supply chain due to port delays have been assessed using quantitative measures in the context of chemical manufacturing based in Singapore (Loh & Thai, 2015). The recent coronavirus outbreak (COVID-19/SARS-CoV-2) has brought severe disruption to the global supply chain (Govindan et al., 2019). In response to COVID-19, different risk mitigation and recovery plans have been proposed to tackle the risks of such outbreaks in the future (Ivanov, 2020). In addition, ecological hazards also disrupt SCM. With this in mind, different models have been proposed to ensure sustainable value creation while taking into account various environmental threats to the supply chain (Klibi et al., 2010). Table 1 details supply chain risks and their factors.

Keeping the aforementioned risks in mind, the current study focuses only on the risk of an epidemic. The risk factor taken into consideration is the COVID-19 pandemic that disrupted the global SCM.

2.2 COVID-19 Pandemic and Disruption in SCM

The novel pandemic outbreak called COVID-19 first originated in Wuhan, a city in China, in late 2019 (Wang et al., 2020). Following the impact and consequences of COVID-19 on human lives, the Chinese government imposed numerous lockdowns in different cities of the country. Meanwhile, within the next few days, multiple cases of COVID-19 were reported in different countries, which alarmed the whole world as it observed the developing epidemic. According to the Worldometer report published in February 2021, more than 107.50 million confirmed cases were reported from all over the world and more than 2.35 million people died due to this epidemic.² Almost all the countries adopted preventive measures, i.e. complete and partial lockdowns.

The lockdowns significantly reduced the economic activities and developed a huge risk for sustaining a continuous supply chain for different business operations (Craighead et al., 2020). Almost every economic sector, i.e. manufacturing and services (Belhadi et al., 2021), agriculture (Workie et al., 2020), food industry (Nakat & Bou-Mitri, 2021), etc. experienced a negative shock due to supply chain disruption because of the COVID-19 pandemic. Different policies have been proposed to hinder the economic losses occurring due to COVID-19 (Gong et al., 2020).

Although these policies were very effective against the spread of COVID-19 pandemic, they instigated different disruption factors in the supply chain network. The pandemic generated the bullwhip effect in supply chains, such as longer lead times, customer demand

² <https://www.worldometers.info/coronavirus/coronavirus-cases/>.

Table 1 Supply chain risks and their factors

S. no.	Main risks	Brief description	Risk factors
1	Natural Disasters	A disastrous event of natural causes	Earthquakes (Tokui et al., 2017) Flooding (Haraguchi & Lall, 2015) Typhoons (Zhang et al., 2020)
2	Terrorism	Violent, illegal deeds committed by a person and/or groups	Unlawful activities (Khan et al., 2018)
3	Cyber attacks	An attempt by hackers to destroy or damage the electronic system	Electronic systems (Simon & Omar, 2020)
4	Epidemics	Damage incurred due to illness or other health-oriented events	COVID-19 (Mahajan & Tomar, 2021)
5	Sovereign risks	Risk arising due to government failure in debt repayment or not fulfilling loan agreements	Cultural differences (Durach et al., 2017) Political instability (Ali et al., 2021) Government regulation (Oke & Gopalakrishnan, 2009)
6	Manufacturing (processual) breakdowns	Failure to progress in the manufacturing process, or any function loss in the process	Production disruptions (Huang et al., 2018) Product design changes (Lin & Zhou, 2011)
7	Inventory risks	Overstocking or stockout of raw materials or final products	Uncertain supply and demand (Schmitt et al., 2015)
8	Port delays	Longer times to ship material goods to their destination	Transportation disruptions (Loh & Thai, 2015) Customs difficulties (Yang, 2011)

swings, product price fluctuations, panic purchasing, etc. (Zighan, 2021). Demand uncertainty impacts the cost structure decision of firms (Kwon, 2019). Several studies revealed that the bullwhip effect can cause poor inventory control, over-hiring or shortage of manpower, and poor customer services (Alabdulkarim, 2020). Additionally, government policies such as confinement also create workforce shortages, along with disruption in the supply and demand cycle (Block et al., 2020).

With this in mind, the current study focuses on the classification of different economic sectors into certain pre-defined classes based on the severity of disruptions produced in SCM due to the COVID-19 pandemic. This classification is performed through a new multi-criteria sorting method. For this, a set of criteria were identified that has the potential to disrupt the SCM under the COVID-19 situation. These criteria have been chosen based on a combined literature review and expert input. In total, 14 experts participated in this research, including engineers, supply chain managers, researchers, and businessmen. The experts were contacted through emails, zoom meetings, physical meetings, and phone calls. In the first step, supply chain disruption criteria were identified in research articles using renowned databases such as Google Scholar, Scopus, and Web of Science. Initially, 16 criteria were identified from the literature as having the potential to disrupt supply chain networks. Next, six criteria were expunged from the list because of their irrelevance to the COVID-19 pandemic

situation or to the case of Pakistan. These irrelevant criteria include mechanical faults in the production process, inappropriate Material Requirement Planning (MRP), failure of the electronic system, i.e. cyberattack, unlawful activities, changes in product or process design, and political instability. Therefore, the experts shortlisted the most relevant and applicable criteria for disruption in the supply chain due to the COVID-19 pandemic in the case of Pakistan. Table 2 shows the shortlisted criteria.

2.3 Sorting based on MCDM

Sorting is defined as a process where items/objects are assigned into pre-defined ordered classes. Multiple studies have been performed to solve sorting problems based on different MCDM approaches.

Yu (1992) developed the first multi-criteria sorting method with direct elicitation of ELECTRE TRI parameters and used the outranking approach (Yu, 1992). Later on, Mousseau and Slowinski (1998) modified the methodology, eliciting the ELECTRE TRI parameters by interacting with multiple respondents (Mousseau & Slowinski, 1998). Subsequently, scholars began to adapt other MCDM approaches such as PROMETHEE, MACBETH, DEA, AHP, UTA, and VIKOR to the sorting methodology to deal with different real-world problems. Hu and Chen proposed a novel PROMETHEE-based classification method to deal with the financial decision problem of bankruptcy prediction using a set of three years (Hu & Chen, 2011). Similarly, another sorting study was performed on financial classification problems using the PROMSORT methodology. They applied the proposed methodology to different failure risks to business and then compared the results with ELECTRE TRI and PROMETHEE TRI (Araz & Ozkarahan, 2005). Besides this, a new sorting method called MACBETHSort was introduced to categorize the strategic products of a firm using ABC classification. The study used the case of a manufacturing firm to validate the MACBETHSort methodology (Ishizaka & Gordon, 2017). Similarly, using the ABC classification strategy, Ishizaka et al. introduced and validated another sorting methodology, DEASort, using the case of the British procurement and logistic firm Entec Global (Ishizaka et al., 2018).

Analytic Hierarchy Process (AHP) has also been adapted to the sorting methodology with AHPSort. The AHPSort significantly reduced the problem-solving time because it requires a fewer number of comparisons compared to AHP. Ishizaka et al. (2012) validated this method of AHPSort using the real-life decision problem of supplier selection (Ishizaka et al., 2012). In 2004, Doumpos and Zopounidis had introduced another algorithm for dealing with the sorting problem called UTADIS, which overcomes the shortcomings of direct elicitation in preferential information affecting the stability and the performance of models (Doumpos & Zopounidis, 2004). Lolli et al. (2015) proposed a sorting methodology known as FlowSort, segregating the failure modes in different priority classes using a Group Decision Support System (GDSS). This FlowSort-GDSS methodology was validated using the dataset of failure modes in the molding process (Lolli et al., 2015).

Despite all these sorting methods based on MCDM approaches, only a few researchers have integrated these methods with fuzzy data. Different studies have investigated the impact of crisp data and fuzzy data on the final ranking in MCDM problems (Ceballos et al., 2017). Furthermore, multiple studies have revealed that the fuzzy technique integrated into MCDM is the most appropriate tool to deal with uncertainty, imprecision, and data vagueness (Kahraman et al., 2015). Therefore, researchers now integrate the fuzzy technique with sorting based on MCDM methods as well. Krejci and Ishizaka (2018) proposed a Fuzzy AHPSort methodology by integrating fuzzy technique with AHPSort. The methodology of Fuzzy AHPSort was

Table 2 Disruption criteria

Criteria	Description of criteria in relation to COVID	References for criteria
Increase in lead times (C1)	Lockdowns and other movement restrictions due to COVID-19 disrupt the supply network, requiring longer delivery times for essentials	Fattahi et al. (2017) Peng et al. (2014)
Increase in raw material prices (C2)	Rises in costs due to the adoption of safety measures, while extracting raw materials and transportation hurdles lead to a surge in raw material prices	Hameri and Hintsu (2009) (Thun and Hoenig (2011)
Bankruptcy of suppliers (C3)	Unexpected disruptions due to COVID-19 engendering financial difficulties for suppliers, which result in supply shortages, disturbing the whole SCM	Li et al. (2016)
Manpower shortages due to an unsuitable working environment (C4)	Many employees move back to their home towns and fear working because of risk of infection	Biswas and Das (2020); (Kumar & Chandra, 2010)
Poor infrastructure (stockpile) (C5)	Companies try to maintain stocks to ensure the smooth flow of business operations, but poor infrastructure or storage space prevent them from doing so	Mohan et al. (2009)
Power breakdowns (C6)	A breakdown in power, i.e. machine failure, electricity blackout, and technical staff are unable to provide immediate services due to COVID-19 restrictions	Yang et al. (2005)
Product price swing (C7)	Uncertain product prices and a shorter life cycle of some products disrupt the SCM	Chopra and Sodhi (2004)
Product demand swing (C8)	Uncertain customer demand from and high holding costs disrupt the SCM	Chopra and Sodhi (2004)
Government Policies (C9)	Standard operating procedures (SOPs) implemented by government agencies increase restrictions on doing business, ultimately disrupting the SCM	Oke and Gopalakrishnan, (2009); Biswas and Das (2020)
High operational cost (fixed + variable cost) (C10)	Due to restrictions, demand of certain products decreases while the operational costs, i.e. fixed costs (shop rents, salaries, etc.) and variable costs (monthly bills, etc.), remain the same, resulting in SCM disruptions	Oke and Gopalakrishnan, (2009)

illustrated using a decision problem of tourism (Krejci & Ishizaka, 2018). Furthermore, another research study proposed AHP-FuzzySort utilizing fuzzy numbers for respondent behavior whereas, crisp numbers for limiting profiles. The proposed AHP-FuzzySort method was implemented to classify the London boroughs based on the safety levels (Ishizaka et al., 2020).

2.4 Research gaps

Recently, many researchers have used VIKOR and fuzzy VIKOR methods to deal with different, complex real-world problems. All these studies reveal that the VIKOR approach has overcome the problem of conflicting criteria and is very effective in a highly complex environment (Mardani et al., 2016). Besides this, Demir et al. (2018) developed a methodology of sorting integrated into the VIKOR approach known as VIKORSort. The proposed VIKORSort was used for selecting the green supplier for electrical equipment manufacturers using crisp values (Demir et al., 2018). However, no study has used fuzzy values with VIKORSort, thus constituting a research gap. Therefore, the major contribution of this study is its deployment of fuzzy set theory with the VIKORSort method to address this research gap.

3 Methodology

This section briefly explains the steps involved in fuzzy VIKORSort. We developed this method by amalgamating three broad concepts, i.e. fuzzy set theory, sorting approach, and VIKOR method. Figure 2 shows the flow chart for this novel method. As illustrated, the fuzzy set theory helps identify the fuzzy weights, fuzzy rating, and fuzzy limit profiles for the criteria used in this study. Later on, we used the VIKOR method to find the S, R, and Q

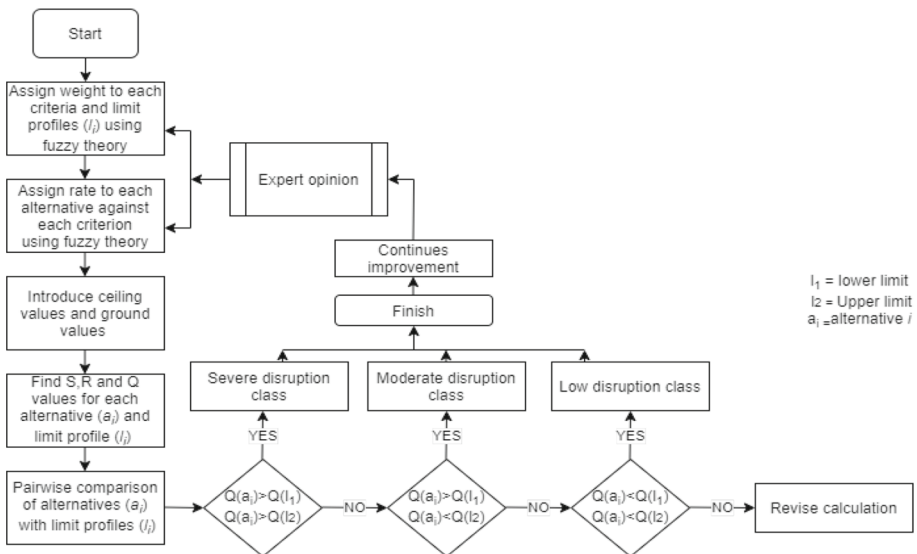


Fig. 2 Methodology Flowchart of sorting based on Fuzzy VIKOR

values, which help in ranking. In the end, the Q values of alternatives and limit profiles are compared to perform the sorting and categorize the economic sectors into predefined classes. For continuous improvement, the expert's opinion should be taken into account constantly concerning the weighting and rating of the criteria under different circumstances.

3.1 Fuzzy rating

Fuzzy set theory is a useful tool in decision problems dealing with the vagueness and ambiguity of data. This theory utilizes linguistic variables and fuzzy numbers. A fuzzy number is a real number having no single fixed value, but rather is linked with a set of possible values. The weights of all these possible sets of values vary between $[0, 1]$ and are known as membership functions. There are several membership functions, but those most commonly used in management studies and supply chains are triangular and trapezoidal membership functions (Kochen, 1975), also known as Triangular/Trapezoidal Fuzzy Number (TFN). Furthermore, there are different point scales used in fuzzy set theory, but the 5-point Likert scale and 7-point Likert scale are the most common. The latter scale provides more accurate results for respondent behavior compared to the 5-point scale (Finstad, 2010). Furthermore, the Likert scale helps in developing decisions, i.e. weighted scoring where respondents evaluate different alternatives utilizing a set of criteria. The weighted scoring method helps calculate overall fuzzy weights and fuzzy ratings. The fuzzy weights and fuzzy ratings are transformed into real numbers using a defuzzification tool. There are several defuzzification tools, where each tool is selected based on the properties of the application (Runkler, 1997). Furthermore, all these defuzzification tools help to convert the output of aggregated fuzzy sets into a single number.

We consider n alternatives; v criteria, t decision-makers, and the number of respondents that assigned the Likert scale point " i " for specific criterion is " t_i^* ". The expressions used to calculate the fuzzy weights of each criterion are:

$$\tilde{W}_{vx} = \frac{1}{t} [(\tilde{w}_{f1} \times t_1^*) + (\tilde{w}_{f2} \times t_2^*) + \dots + (\tilde{w}_{f7} \times t_7^*)] \quad (1)$$

Here, \tilde{W}_{vx} represents the overall fuzzy weight for the criterion " v " and " x " value in a triangular membership function ($x = a, b, c$) or ($x = \text{lower value, middle value, upper value}$) whereas, \tilde{w}_{fy} represents the fuzzy value for each point in the Likert scale ($y = 1, 2, \dots, 7$). After calculating all the fuzzy values of the triangular membership function for each criterion, the values are then defuzzified. The defuzzification is performed using the centroid method named Best Non-fuzzy Performance (BNP) (Chang & Wang, 2009).

$$\text{BNP}_i = \frac{[(c - a) + (b - a)]}{3} + a \quad (2)$$

The fuzzy rating or the importance of specific alternatives to a criterion is calculated using the following expression;

$$\tilde{R}_{vxi} = \frac{1}{t} [(\tilde{w}_{fxi} \times t_{vi1}^*) + (\tilde{w}_{f2} \times t_{vi2}^*) + \dots + (\tilde{w}_{f7} \times t_{vi7}^*)] \quad (3)$$

Here, \tilde{R}_{vxi} represents the overall fuzzy rate for alternative " i " against the criterion " v ". Similarly, \tilde{w}_{fy} represents the fuzzy value for each point in the Likert scale ($y = 1, 2, \dots, 7$), whereas t_{viy}^* represents the respondents that assigned the Likert scale point " y " for alternative " i " as regards criterion " v ". Moreover, the same BNP formula (2) is used for the defuzzification of fuzzy rate values.

Further steps of the methodology are performed through the sorting approach and the VIKOR method. The integration of Fuzzy set theory with the sorting approach and VIKOR method is the novelty of our study.

3.2 Sorting approach

In sorting problems, alternatives are classified into predefined classes. This classification is performed based on limit profiles. For “z” predefined classes, the number of limit profiles will be “z-L”.

For this sorting approach, the respondents are asked to assign values to limit profile using the Likert scale. These fuzzy values for limit profiles are transformed into real numbers using the fuzzy set theory method. The fuzzy weights are calculated using Eq. 1. The limit profiles calculated using the fuzzy set theory are the added innovation of this research study.

3.3 Steps of fuzzy VIKORSort method

Step 1 Calculate a decision matrix that contains aggregated weights and rating values using Eqs. 1, 2, and 3.

$$\tilde{W} = \tilde{w}_1, \tilde{w}_2, \tilde{w}_3 \dots \tilde{w}_L \tag{4}$$

$$\tilde{R} = \begin{bmatrix} \tilde{g}_{11} & \tilde{g}_{12} & \dots & \tilde{g}_{1u} \\ \vdots & \cdot & \ddots & \vdots \\ \tilde{g}_{v1} & \tilde{g}_{v2} & \dots & \tilde{g}_{vn} \end{bmatrix} \tag{5}$$

Here, \tilde{W} represents the vector of fuzzy weights, whereas \tilde{R} denotes the decision matrix for the fuzzy rating. The \tilde{g}_{vn} shows the fuzzy rating value for criterion “v” against the alternative “n”. Here, $\tilde{g}_{vn} = (l_{vn}, m_{vn}, r_{vn})$, whereas we define $\tilde{w}_L = (l_v, m_v, r_v)$ as a TFN.

Step 2 Decision vectors are constructed for aggregated weights of limit profiles.

$$\tilde{L}_1 = \tilde{l}_1, \tilde{l}_2, \tilde{l}_3 \dots \tilde{l}_{vn} \tag{6}$$

$$\tilde{L}_2 = \tilde{l}_1, \tilde{l}_2, \tilde{l}_3 \dots \tilde{l}_{vn} \tag{7}$$

Here, the decision vectors constructed are for two limit profiles against respective alternatives, i.e. lower limit or L_1 and upper limit or L_2 , whereas \tilde{l}_{vn} represents the limit profile value for criterion v regarding alternative n. Here, we define $\tilde{l}_{vn} = (l_{vn}, m_{vn}, r_{vn})$ as a TFN.

Step 3 Find the ceiling and ground values for each criterion. The ceiling value is the highest possible value whereas, the ground value is the smallest possible value on the Likert scale used for this study. These values are absolute and are independent of the alternatives; this means that the classification does not depend on the available alternatives.

Step 4 Select the positive ideal solution or best $\tilde{f}_i^* = (l_v^*, m_v^*, r_v^*)$ and the negative ideal solution or worst $\tilde{f}_i^- = (l_v^-, m_v^-, r_v^-)$. In most of the decision problems, the values of best and worst f_i change, i.e. we choose the maximum value for the positive criterion and the minimum value for the negative criterion. However, in the case of limit profiles, as we are classifying the alternatives in certain predefined classes, i.e. severe, moderate, and low disruptions, we will take maximum for best f_i^* and minimum for f_i^- for all criterion and limit profiles. Furthermore, as the calculation is absolute, \tilde{f}_i^* will be the ceiling value, whereas \tilde{f}_i^- will be

the ground value. The mathematical relation used for this step is as follows:

$$\tilde{f}_i^* = \max_j(l_v^*, m_v^*, r_v^*) \quad (8)$$

$$\tilde{f}_i^- = \min_j(l_v^*, m_v^*, r_v^*) \quad (9)$$

Here, v represents the criterion for the j alternative.

Step 5 Calculate the values of \tilde{S}_k and \tilde{R}_k for all alternatives and limit profiles using the mathematical relations.

$$\tilde{S}_k = \sum_{i=1}^n w_i (f_i^* - f_{ki}) / (f_i^* - f_i^-) \quad (10)$$

$$\tilde{R}_k = \max_{i=1}^n w_i (f_i^* - f_{ki}) / (f_i^* - f_i^-) \quad (11)$$

Here, w_i represent relative importance calculated as the weight of each criterion. Here, we define the $\tilde{S}_k = (S_n^l, S_n^m, S_n^r)$ and $\tilde{R}_k = (R_n^l, R_n^m, R_n^r)$ as a TFN.

Step 6 Find the value of Q_k for each alternative and limit profiles. The value of Q_k is computed using the following equation:

$$Q_k = \frac{v(S_k - S^*)}{(S^- - S^*)} + \frac{(1 - v)(R_k - R^*)}{(R^- - R^*)} \quad (12)$$

Here,

$$\tilde{S}^* = \min_i S_k \quad (13)$$

$$\tilde{S}^- = \max_i S_k \quad (14)$$

And,

$$\tilde{R}^* = \min_i R_k \quad (15)$$

$$\tilde{R}^- = \max_i R_k \quad (16)$$

where “ v ” in Eq. 12 represents the weight of the strategy and its value varies between [0,1]. Here we define the $\tilde{Q}_k = (Q_n^l, Q_n^m, Q_n^r)$ as a TFN.

It is important to mention that we ranked the alternatives using the three S, R, and Q indexes. Here, the variable ‘S’ characterizes the aggregated value of the distances of the criteria, whereas the variable ‘R’ denotes the maximum distance of the criteria from the fuzzy best value, respectively. The fuzzy best value represents the utmost desirable value for each criterion. Afterward, these values of ‘S’ and ‘R’ are used to calculate the value of ‘Q’ for each alternative that provides the basis for the final ranking.

Step 7 Defuzzify the S, R, and Q values of each alternative and limit profile using Eq. (2).

Step 8 Rank all the values of S, R, and Q in ascending order.

Step 9 Sort the available alternatives into the desired predefined classes. The sorting is performed using the Q value ranking of alternatives and limit profiles. The rank of the Q value for each limit profile provides the basis for classifying each alternative into a predefined class.

4 Case study

The proposed methodology, i.e. Fuzzy VIKORSort was employed to assess company resilience to disruption in a supply chain due to the COVID-19 pandemic in Pakistan. Furthermore, based on the disruptions, the companies are categorized into three disruption classes (severe, moderate, and low), for which we defined two limit profiles (L1 and L2). For this purpose, we identified 10 criteria from different sources (literature, reports, and consulting with professionals) as having the potential to disrupt the SCM, whereas the economic sectors act as alternatives.

4.1 Data collection

We collected the data for this research through an online survey. For this, a questionnaire was developed to perform the survey among different expert groups belonging to Pakistan and working in different economic sectors. The questionnaire was comprised of four different sections. The first section ascertained the demographic of the respondent, the second section sought to weight each criterion according to its participation in the disruption of SCM, the third section assigned limit profiles to each criterion, and the final section rated each criterion against a specific economic sector and considering the supply chain disruptions and the COVID-19 pandemic. The questionnaires of all four sections are shown in Appendix 1.

We designed the questionnaires in a Google form and shared the link with around 150 professionals working in different economic sectors in Pakistan. These professionals include engineers, logistics and supply chain managers, freelancers, procurement managers, or businessmen. After two to three reminders through emails, phone calls, and text messages to each professional over several weeks, we received 63 responses to our questionnaires. Each response was double-checked so that we could eliminate the irrelevant (the professionals who are no longer working in Pakistan) and the incorrect (those giving the same values to all criteria without any serious concentration on the questions). Moreover, we eliminated the economic sector having one or two respondents to increase the reproducibility of the final results. After filtration, a sample of 49 respondents remained, to which data analysis was applied using the Fuzzy VIKORSort methodology. The details of the number of professionals for each economic sector are shown in Table 3.

Table 3 Total number of Experts

Economic sector	No. of respondents
Manufacturing sector (MANU)	17
Wholesaler and Retailer sector (WS&R)	5
Accommodation and Foodservices sector (A&F)	8
Energy sector (ES)	5
Construction sector (CONS)	9
Information and Communication Technology sector (ICT)	5

5 Result and discussion

The analysis was performed in multiple steps using the Fuzzy VIKORSort methodology. Firstly, the weight for each criterion was identified using the fuzzy set theory method. We show the weights in Table 4. The weight value for each criterion represents its contribution to the SCM disruption. From Table 4, the increase in lead time with the highest weight value is a major cause of disruption in the supply chain followed by high operational costs and government policies. However, the manpower shortage due to an unsuitable working environment and poor infrastructure are the least contributing criterion to supply chain disruption.

Secondly, we calculated the fuzzy limit profiles, i.e. L1 and L2, for each criterion, providing the basis for categorizing the economic sectors into three predefined classes. We show the fuzzy limit profile values in Table 5. From Table 5, the increase in lead time has the highest fuzzy value for the upper limit, followed by high operational cost, and government policies. The criterion with high upper limits is sensitive, which means that a slight disturbance in that criterion produces a far-reaching high order impact on the whole supply chain network. On the other hand, a breakdown in power has the smallest fuzzy value for the lower limit, followed by MSIWE. The smaller fuzzy value for the lower limit indicates a comparatively less frequent criterion that disrupts the supply chain network.

Thirdly, we calculated the ceiling and ground values, which we then used as the best crisp value (\tilde{f}_i^*) and worst crisp value (\tilde{f}_i^-), respectively. While the conventional VIKOR method calculates the best and worst crisp values are with the relative approach, our Fuzzy VIKORSort method introduces the absolute approach using ceiling and ground values. Table 6 shows the ceiling and ground values for each criterion.

Fourth, the S, R, and Q values are calculated for each alternative and limit profile. Table 7 represents the S and R values along with ranking; Table 8 represents the Q values with ranking for each alternative and limit profile.

The allocation of each alternative in a predefined class is based on its Q value. The results show that A&F is the most affected sector among the available alternatives, followed by CONS, with defuzzified Q values of 0.00 and 0.029, respectively. Both of these sectors are categorized as severe disruption class. However, the supply chain of Info & Com experienced

Table 4 Criterion weights

Criteria	Fuzzified weight value	Defuzzified weight value
Increase in lead time	0.680, 0.855, 0.959	0.831
Increase in raw material prices	0.612, 0.790, 0.910	0.771
Bankruptcy of suppliers	0.549, 0.724, 0.863	0.712
Manpower shortage due to an unsuitable working environment	0.502, 0.688, 0.839	0.676
Poor infrastructure	0.514, 0.696, 0.845	0.685
Power breakdowns	0.553, 0.735, 0.876	0.721
Product price swings	0.549, 0.735, 0.876	0.720
Product demand swings	0.588, 0.765, 0.894	0.749
Government policies	0.627, 0.796, 0.906	0.776
High operational costs (fixed + variable costs)	0.653, 0.814, 0.912	0.793

Table 5 Limit profiles

Criteria	Lower limit	Upper limit
Increase in lead time	0.329, 0.508, 0.690	0.627, 0.816, 0.945
Increase in raw material prices	0.357, 0.537, 0.712	0.602, 0.788, 0.920
Bankruptcy of suppliers	0.304, 0.478, 0.665	0.608, 0.798, 0.927
Manpower shortage due to an unsuitable working environment	0.294, 0.463, 0.643	0.555, 0.743, 0.892
Poor infrastructure	0.300, 0.482, 0.665	0.561, 0.753, 0.900
Power breakdowns	0.273, 0.445, 0.635	0.514, 0.702, 0.855
Product price swings	0.333, 0.506, 0.684	0.594, 0.782, 0.914
Product demand swings	0.322, 0.498, 0.673	0.594, 0.780, 0.920
Government policies	0.337, 0.506, 0.673	0.629, 0.808, 0.927
High operational costs (fixed + variable costs)	0.341, 0.518, 0.696	0.622, 0.810, 0.945

Table 6 Ceiling and ground values

Criteria	Ceiling value	Ground value
Increase in lead time	0.9, 1, 1	0, 0, 0.1
Increase in raw material prices	0.9, 1, 1	0, 0, 0.1
Bankruptcy of suppliers	0.9, 1, 1	0, 0, 0.1
Manpower shortage due to an unsuitable working environment	0.9, 1, 1	0, 0, 0.1
Poor infrastructure	0.9, 1, 1	0, 0, 0.1
Power breakdowns	0.9, 1, 1	0, 0, 0.1
Product price swings	0.9, 1, 1	0, 0, 0.1
Product demand swings	0.9, 1, 1	0, 0, 0.1
Government policies	0.9, 1, 1	0, 0, 0.1
High operational costs (fixed + variable costs)	0.9, 1, 1	0, 0, 0.1

fewer perturbations due to the COVID-19 pandemic, which categorizes it as a low disruption class with the highest defuzzified Q value, i.e. 1.00. All other alternatives, i.e. MANU, WSRT, and Energy, are categorized as moderate disruption classes, having defuzzified Q values of 0.077, 0.079, and 0.174, respectively.

Table 7 Ranking with S and R values

Alternatives	Fuzzified S-value	Defuzzified S-value	Ranking with S-value	Fuzzified R-values	Defuzzified R-values	Ranking with R-value
MANU	6.241, 6.324, 3.587	5.727	5	0.774, 0.869, 0.598	0.747	4
WS&R	6.005, 6.077, 3.594	5.537	4	0.830, 0.918, 0.657	0.802	5
A&F	4.276, 3.651, 1.002	3.496	1	0.496, 0.456, 0.160	0.371	1
Energy	9.028, 10.245, 7.601	8.986	6	1.027, 1.259, 1.063	1.117	7
CONS	4.457, 3.930, 1.438	3.748	2	0.707, 0.755, 0.462	0.641	3
Info & Com	24.230, 33.354, 33.054	27.819	8	4.893, 6.841, 6.906	6.213	8
L1	9.523, 10.817, 8.159	9.509	7	1.075, 1.167, 0.885	1.043	6
L2	5.522794, 5.163431, 2.315237	4.809	3	0.626, 0.642, 0.372	0.547	2

Table 8 Ranking with Q-values and disruption classes

Alternative	Fuzzified Q-value	Defuzzified Q-value	Ranking with Q-value	Disruption class
MANU	0.081, 0.077, 0.073	0.077	4	Moderate
WS&R	0.081, 0.077, 0.077	0.079	5	Moderate
A&F	0.000, 0.000, 0.000	0.000	1	Severe
Energy	0.179, 0.174, 0.170	0.174	6	Moderate
CONS	0.029, 0.028, 0.029	0.029	2	Severe
Info & Com	1.000, 1.000, 1.000	1.000	8	Low
L1	0.197, 0.176, 0.165	0.180	7	
L2	0.046, 0.040, 0.036	0.041	3	

5.1 Discussion

The final results show that the economic sectors are categorized into three predefined groups based on Q-values calculated with fuzzy VIKORSort, which was the major objective of

this study. Each predefined group is then discussed based on economic sector, respondent demographics, and the level of disruptions generated due to the COVID-19 pandemic.

5.1.1 Severe disruption class

The data collected from the experts in the accommodation and food sector are mostly from CEOs of the different fast-food chains and well-known hotels in Pakistan. Over the last few decades, rapid growth in fast food restaurants, i.e. 20% annually, is observed, which makes it the second largest industry in Pakistan. (Memon, 2016). Furthermore, an average consumer in Pakistan spends around 42% of their earnings on food and is more inclined to visit restaurants instead of cooking at home. However, due to fear of the COVID-19 pandemic, the government of Pakistan adopted a lockdown policy and closed all public places and food areas completely. Although many enterprises such as fast food vendors, restaurants, bakeries, and other related sectors started taking online orders and home deliveries with maximum possible safety measures, the results were unsatisfactory. Furthermore, the failure of the Pakistan government to provide a bailout package for such small businesses further worsened their economic conditions. Therefore, the increase in lead time and government policies was the major cause of severe disruption in the supply chain of A&F. All the defuzzified rating values of A&F are shown in Table 9 of Appendix 2.

The professionals working in the construction sector and who participated in this research study are mostly engineers, assistant managers, managers, and contractors. The CONS also experienced severe disruptions due to the COVID-19 pandemic in Pakistan. The shortage of raw material and increase in lead time was the major challenge. According to INTERCEM, within the first 15 days of lockdown in Pakistan, 11 cement manufacturing plants closed completely out of a total of 25, whereas the remaining 14 moved into a partial shutdown phase. Furthermore, cement sales per day in Pakistan dropped from 160,000 tons to only 35,000 tons.³ Normally, the steel manufacturers in Pakistan mostly imported the raw material from China in containers; due to the high number of COVID-19 cases in China, Pakistan closed its border with China and all the economic activities between both countries ceased. Therefore, the increase in lead time, along with a decrease in sales, resulted in high operational costs, which ultimately stopped different production units. All the defuzzified rating values of CONS are shown in Table 9 of Appendix 2.

5.1.2 Moderate disruption class

The experts from the manufacturing sector who participated in this research are mainly engineers, procurement managers, and supply chain managers. The MANU of Pakistan contributes around 13 percent of its total Gross Domestic Product (GDP). Many products manufactured in Pakistan, especially sports equipment, garments, chemicals, etc., are exported to different countries across the globe. However, the closure of borders due to COVID-19 drastically reduced the export orders. Furthermore, many manufacturing firms stopped their production because of high operational costs due to a decrease in sales and an increase in raw material prices such as steel, pharmaceutical, and many others. On the other hand, some manufacturing industries took COVID-19 as an opportunity to grow during this period, especially health safety products and some packaging industries. For instance, the manufacturing of masks and sanitizers grew very fast because of high demand. Furthermore, the demand

³ <https://www.intercem.com/InterCem-Insights/News/ArtMID/683/ArticleID/1818/Covid-19-it%E2%80%99s-impact-on-Pakistan%E2%80%99s-cement-sector>.

for different staple foods in packages such as rice, cereals, milk, fish, cheese, etc., boosted the demand of the packaging industry. All the defuzzified rating values of MANU are shown in Table 9 of Appendix 2.

The respondents from wholesalers and retailers who participated in this research study are business owners and wholesale managers. The wholesale and retail sector in Pakistan also experienced adverse effects because of preventive measures, i.e. lockdowns, which were adopted to stop the spread of the COVID-19 pandemic. These lockdowns increased the order lead time, causing the retailer to lose many customer orders. Furthermore, another common challenge faced by retailers was high operational costs due to a decrease in sales. The customers were unable to visit different retail stores and supermarkets because of a stay-at-home policy announced by the government which, left the retailers with unsold stocks. According to the UNIDO report, many wholesale and retail markets in Pakistan were closed, including Badami Bagh – a leading auto retail store in Pakistan – because of low sales and high operating costs.⁴ On the other hand, to improve sales performance, some retailers in Pakistan started selling their products on social media platforms, i.e. Facebook, etc. All the defuzzified rating values of WS&R are shown in Table 9 of Appendix 2.

The professionals from the energy sector who participated in this research are engineers (petroleum, chemical) and procurement managers. The findings of our research show that a manpower shortage due to the unsuitable working environment was the major challenge for the ES, followed by poor infrastructure and product demand swings. The unprecedented lockdowns and other preventive government-implemented measures forced the refineries, coal mines, and excavating contractors to decrease the number of workers in a shift. Furthermore, the energy demand also fell because of a decline in economic activities, i.e. reduction in air travel and the complete and partial closure of industrial units (Iqbal et al., 2021). All the defuzzified rating values of ES are shown in Table 9 of Appendix 2.

5.1.3 Low disruption class

The respondents of the information and communication sector who participated in this research are software engineers, computer engineers, and freelancers. These experts are working mainly in software houses on different online projects. Unlike many other economic sectors, the disruption in the supply chain due to the COVID-19 pandemic in ICT is very low because of the online flow of information and order delivery. The common problem faced by many experts of ICT was poor infrastructure and power breakdowns, which were also assigned smaller fuzzy weights in disruption of the supply chain. In poor infrastructure, employees faced poor internet facilities while working from home. Furthermore, the energy crisis in Pakistan generated power breakdown, representing a very serious threat of ICT supply chain disruption. All the defuzzified rating values of ICT are shown in Table 9 of Appendix 2.

5.1.4 Managerial implications

The findings of this research using the proposed Fuzzy VIKORSort methodology provide interesting managerial insights. Firstly, these findings will help authorities take preventive measures to mitigate the hazardous impact of any uncertain event in the future to safeguard the economic sectors from unexpected losses. For instance, the managers and planners should

⁴ https://www.unido.org/sites/default/files/files/2021-03/UNIDO%20COVID19%20Assessment_Pakistan_FINAL.pdf.

emphasize highly disrupted economic sectors in managing potential threats and regularly identify the economic order quantity, taking into account the lead times and demand fluctuations in such crucial environments. Furthermore, these findings will help policymakers focus on highly disrupted economic sectors and provide relief to business owners, such as tax relaxation, subsidies on certain products, and low interest or interest-free loans. Doing so will ease not only doing business, but also minimize the impact of criteria contributing highly to disruptions, i.e. raw material prices, government policies, and high operational costs.

Secondly, although the case discussed in this study is supply chain disruption due to the COVID-19 pandemic, managers can use the same methodology for any decision involved in sorting problems. For instance, this method can be used for selecting suppliers, hiring employees, investment opportunities, etc., to classify the available alternatives into best and worst groups before making the decision.

6 Conclusion and future research direction

Over the past two years, the COVID-19 outbreak exposed the vulnerabilities associated with the current supply chain. This outbreak produced supply chain disruptions generating widespread impact on all economic activities across the globe. To stop the rapid propagation of the virus, all the countries adopted preventive measures, which disturbed all business operations. The impact of these preventive measures on the supply chain was especially critical in frugal economies like Pakistan. It is important, therefore, to develop an effective action plan to analyze the losses incurred by each economic sector due to such disruptions. Furthermore, to prioritize this action plan, a full-fledged methodology is essential to categorize the economic sectors based on the disruption losses. With this in mind, this study contributes to the literature by proposing a novel Fuzzy VIKORSort methodology that categorizes the economic sectors into certain predefined, ordered classes.

The findings of this study are helpful in identifying the most vulnerable sectors in the face of unlikely events. For instance, the case discussed in this research revealed that the supply chain of the accommodation and food sector, along with the construction sector, is the most vulnerable sector in the COVID-19 pandemic in Pakistan. These results can help policymakers and government officials design a recovery plan for whenever such an unlikely event happens. For example, the authorities can adopt different measures such as well-maintained buffer stock, self-sufficient and minimally dependent on imports from other countries, which may help to shield the supply chain from disruption during global, destructive events. Additionally, well-trained marketing experts should be hired who can access and fulfill the demands of at-home customers and also update them about new offerings.

No study is without its limitations. Our study utilized only 10 different potential risks to SCM during the COVID-19 pandemic. Future research might include many other risks not identified here. Furthermore, the current study classified only six economic sectors of Pakistan based on disruptions produced in SC due to the COVID-19 pandemic, whereas many other economic sectors still need the attention of researchers for their classification. Similarly, many other countries can adopt the same methodology to classify their economic sectors into predefined classes and design preventive policy measures. Above all, the application of this methodology can be extended to other natural and manmade disasters.

Appendix 1

Demographic questions

What is your profession? *

Assistant Manager

Please specify the country where you are working or did work. (Please note that you must fill the complete survey in the perspective of the country you are working or did work) *

Pakistan

In which economic sector are you working or did work? *

Manufacturing sector

Wholesale and Retailer sector

Accommodation and Foodservices sector

Education and Health services sector

Construction sector

Information and Communication Technology sector

Other: _____

Please assign the weight to each criterion based on its role in disrupting the Supply Chain of the economic sector you work in. For example, if a criterion highly disrupts the supply chain of a sector, then assign a weight of Very High, and if a criterion least affects the supply chain of a sector, then assign a weight of Very Low.

Assign Weights *

	Very High	High	Medium High	Medium	Medium Low	Low	Very Low
Increase in lead time	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Increase in raw material prices	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Bankruptcy of suppliers	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Manpower shortage due to an unsuitable working environment	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Poor infrastructure (stockpile)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Power breakdowns	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Product price swings	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Product demand swings	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Government Policies	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
High operational costs (fixed + variable costs)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Assign the minimum possible value for each criterion to be in Severe disruption class (Please note that the minimum possible value for Severe disruption class must be higher than the minimum possible value for Moderate disruption class) *

	Very High	High	Medium High	Medium	Medium Low	Low	Very Low
Increase in lead time	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Increase in raw material prices	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Bankruptcy of suppliers	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Manpower shortage due to an unsuitable working environment	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Poor infrastructure (stockpile)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Power breakdowns	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Product price swings	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Product demand swings	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Government Policies	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
High operational costs (fixed + variable costs)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Assign the minimum possible value for each criterion to be in Moderate disruption class (Please note that the minimum possible value for Moderate disruption class must be smaller than the minimum possible value for Severe disruption class) *

	Very High	High	Medium High	Medium	Medium Low	Low	Very Low
Increase in lead time	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Increase in raw material prices	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Bankruptcy of suppliers	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Manpower shortage due to an unsuitable working environment	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Poor infrastructure (stockpile)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Power breakdowns	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Product price swings	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Product demand swings	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Government Policies	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
High operational costs (fixed + variable costs)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Assign Rate to each Criterion keeping your economic sector and COVID19 Pandemic under consideration. *

	Very High	High	Medium High	Medium	Medium Low	Low	Very Low
Increase in lead time	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Increase in raw material prices	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Bankruptcy of suppliers	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Manpower shortage due to an unsuitable working environment	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Poor infrastructure (stockpile)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Power breakdowns	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Product price swings	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Product demand swings	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Government Policies	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
High operational costs (fixed + variable costs)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Appendix 2

See Table 9.

Table 9 Defuzzified rating

Criteria	Defuzzified rating					
	A&F	CONS	MANU	WS&R	ES	ICT
Increase in lead times	0.883	0.904	0.755	0.927	0.547	0.220
Increase in raw material prices	0.871	0.804	0.788	0.820	0.540	0.273
Bankruptcy of suppliers	0.825	0.767	0.678	0.627	0.573	0.227
Manpower shortages due to an unsuitable working environment	0.817	0.770	0.712	0.540	0.667	0.220
Poor infrastructure	0.817	0.656	0.624	0.540	0.573	0.220
Power breakdowns	0.763	0.589	0.582	0.500	0.520	0.240
Product price swings	0.783	0.859	0.735	0.747	0.540	0.280
Product demand swings	0.908	0.889	0.743	0.800	0.560	0.280
Government policies	0.867	0.900	0.757	0.740	0.540	0.260
High operational costs (fixed + variable costs)	0.854	0.944	0.835	0.893	0.560	0.240

References

- Alabdulkarim, A. (2020). Minimizing the bullwhip effect in a supply chain: A simulation approach using the beer game. *SIMULATION*, *96*(9), 737–752.
- Ali, S., Paul, S., Chowdhury, P., Agarwal, R., Fathollahi-Fard, A., Jabbour, C., & Luthra, S. (2021). Modelling of supply chain disruption analytics using an integrated approach: An emerging economy example. *Expert Systems with Applications*, *173*, 114690.
- Alsharef, A., Banerjee, S., Uddin, S., Albert, A., & Jaselskis, E. (2021). Early impacts of the COVID-19 pandemic on the United States construction industry. *International Journal of Environmental Research and Public Health*, *18*(4), 1559.
- Ammar, S., & Wright, R. (2000). Applying fuzzy-set theory to performance evaluation. *Socio-Economic Planning Sciences*, *34*(4), 285–302.
- Anderson, R., Heesterbeek, H., Klinkenberg, D., & Hollingsworth, T. (2020). How will country-based mitigation measures influence the course of the COVID-19 epidemic? *The Lancet*, *395*(10228), 931–934.
- Anser, M., Khan, M., Nassani, A., Abro, M., Zaman, K., & Kabbani, A. (2021). Does COVID-19 pandemic disrupt sustainable supply chain process? Covering some new global facts. *Environmental Science and Pollution Research*. <https://doi.org/10.1007/s11356-021-14817-2>
- Araz, C., & Ozkarahan, I. (2005). A multicriteria sorting procedure for financial classification problems: The case of business failure risk assessment. In *International Conference on Intelligent Data Engineering and Automated Learning*.
- Belhadi, A., Kamble, S., Jabbour, C., Gunasekaran, A., Ndubisi, N., & Venkatesh, M. (2021). Manufacturing and service supply chain resilience to the COVID-19 outbreak: Lessons learned from the automobile and airline industries. *Technological Forecasting and Social Change*, *163*, 120447.
- Biswas, T., & Das, M. (2020). Selection of the barriers of supply chain management in Indian manufacturing sectors due to COVID-19 impacts. *Operational Research in Engineering Sciences: Theory and Applications*, *3*(3), 1–12.
- Block, P., Hoffman, M., Raabe, I., Rahal, C., Kashyap, R., & Mills, M. (2020). Social network-based distancing strategies to flatten the COVID-19 curve in a post-lockdown world. *Nature Human Behaviour*, *4*(6), 588–596.
- Boyaci-Gunduz, C., Ibrahim, S., Wei, O., & Galanakis, C. (2021). Transformation of the food sector: Security and resilience during the COVID-19 pandemic. *Foods*, *10*(3), 497.
- Ceballos, B., Lamata, M., Pelta, D., & Yager, R. (2018). Crisp vs. fuzzy data in multicriteria decision making: The case of the VIKOR method. In J. Kacprzyk, E. Szmidt, S. Zadrozny, K. T. Atanassov, & M. Krawczak (Eds.), *Advances in intelligent systems and computing* (pp. 455–465). Springer.
- Ceballos, B., Pelta, D., & Lamata, M. (2018). Rank reversal and the VIKOR method: An empirical evaluation. *International Journal of Information Technology & Decision Making*, *17*(02), 513–525.
- Chang, T., & Wang, T. (2009). Using the fuzzy multi-criteria decision making approach for measuring the possibility of successful knowledge management. *Information Sciences*, *179*(4), 355–370.
- Chopra, S., & Sodhi, M. (2004). Supply-chain breakdown. *MIT Sloan Management Review*, *46*(1), 53–61.
- Chowdhury, P., Paul, S., Kaisar, S., & Moktadir, M. (2021). COVID-19 pandemic related supply chain studies: A systematic review. *Transportation Research Part E: Logistics and Transportation Review*, *148*, 102271.
- Christopher, M., & Peck, H. (2004). Building the resilient supply chain. *International Journal of Logistics Management*, *15*(2), 1–13.
- Christopher, M., Peck, H., & Towill, D. (2006). A taxonomy for selecting global supply chain strategies. *The International Journal of Logistics Management*, *17*(2), 277–287.
- Craighead, C., Ketchen, D., Jr., & Darby, J. (2020). Pandemics and supply chain management research: Toward a theoretical toolbox. *Decision Sciences*, *51*(4), 838–866.
- Demir, L., Akpınar, M., Araz, C., & Ilgin, M. (2018). A green supplier evaluation system based on a new multi-criteria sorting method: VIKORSORT. *Expert Systems with Applications*, *114*, 479–487.
- Doumpos, M., & Zopounidis, C. (2004). Developing sorting models using preference disaggregation analysis: An experimental investigation. *European Journal of Operational Research*, *154*(3), 585–598.
- Dowdy, R., & Wallace, W. (2010). Implications of organizational culture for supply chain disruption and restoration. *International Journal of Production Economics*, *126*(1), 57–65.
- Durach, C., Glasen, P., & Straube, F. (2017). Disruption causes and disruption management in supply chains with Chinese suppliers. *International Journal of Physical Distribution & Logistics Management*, *47*(9), 843–863.
- Eckstein, D., Hutfils, M. L., & Wings, M. (2021). *Global climate risk index 2021. Who suffers most from extreme weather events*. Germanwatch.

- Fattahi, M., Govindan, K., & Keyvanshokoo, E. (2017). Responsive and resilient supply chain network design under operational and disruption risks with delivery lead-time sensitive customers. *Transportation Research Part E: Logistics and Transportation Review*, 101, 176–200.
- Finstad, K. (2010). Response interpolation and scale sensitivity: Evidence against 5-point scales. *Journal of Usability Studies*, 5(3), 104–110.
- Gong, B., Zhang, S., Yuan, L., & Chen, K. (2020). A balance act: Minimizing economic loss while controlling novel coronavirus pneumonia. *Journal of Chinese Governance*, 5(2), 249–268.
- Govindan, K., Mina, H., & Alavi, B. (2020). A decision support system for demand management in healthcare supply chains considering the epidemic outbreaks: A case study of coronavirus disease 2019 (COVID-19). *Transportation Research Part E: Logistics and Transportation Review*, 138, 101967.
- Habermann, M., Blackhurst, J., & Metcalf, A. (2015). Keep your friends close? Supply chain design and disruption risk. *Decision Sciences*, 46(3), 491–526.
- Hameri, A., & Hintsala, J. (2009). Assessing the drivers of change for cross-border supply chains. *International Journal of Physical Distribution & Logistics Management*, 39(9), 741–761.
- Haraguchi, M., & Lall, U. (2015). Flood risks and impacts: A case study of Thailand's floods in 2011 and research questions for supply chain decision making. *International Journal of Disaster Risk Reduction*, 14, 256–272.
- Hu, Y., & Chen, C. (2011). A PROMETHEE-based classification method using concordance and discordance relations and its application to bankruptcy prediction. *Information Sciences*, 181(22), 4959–4968.
- Huang, H., He, Y., & Li, D. (2018). Pricing and inventory decisions in the food supply chain with production disruption and controllable deterioration. *Journal of Cleaner Production*, 180, 280–296.
- Iqbal, S., Bilal, A., Nurunnabi, M., Iqbal, W., Alfakhri, Y., & Iqbal, N. (2021). It is time to control the worst: Testing COVID-19 outbreak, energy consumption and CO₂ emission. *Environmental Science and Pollution Research*, 28(15), 19008–19020.
- Ishizaka, A., & Gordon, M. (2017). MACBETHSort: A multiple criteria decision aid procedure for sorting strategic products. *Journal of the Operational Research Society*, 68(1), 53–61.
- Ishizaka, A., Lolli, F., Balugani, E., Cavallieri, R., & Gamberini, R. (2018). DEASort: Assigning items with data envelopment analysis in ABC classes. *International Journal of Production Economics*, 199, 7–15.
- Ishizaka, A., Pearman, C., & Nemery, P. (2012). AHPSort: An AHP-based method for sorting problems. *International Journal of Production Research*, 50(17), 4767–4784.
- Ishizaka, A., Tasiou, M., & Martinez, L. (2020). Analytic hierarchy process-fuzzy sorting: An analytic hierarchy process-based method for fuzzy classification in sorting problems. *Journal of the Operational Research Society*, 71(6), 928–947.
- Ivanov, D. (2020). Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case. *Transportation Research Part E: Logistics and Transportation Review*, 136, 101922.
- Juergensen, J., Guimon, J., & Narula, R. (2020). European SMEs amidst the COVID-19 crisis: Assessing impact and policy responses. *Journal of Industrial and Business Economics*, 47(3), 499–510.
- Kahraman, C., Onar, S., & Oztaysi, B. (2015). Fuzzy multicriteria decision-making: A literature review. *International Journal of Computational Intelligence Systems*, 8(4), 637–666.
- Khan, A., Estrada, M., & Yusof, Z. (2016). How terrorism affects the economic performance? The case of Pakistan. *Quality & Quantity*, 50(2), 867–883.
- Khan, M., Akhtar, P., & Merali, Y. (2018). Strategies and effective decision-making against terrorism affecting supply chain risk management and security: A novel combination of triangulated methods. *Industrial Management & Data Systems*, 118(7), 1528–1546.
- Kleindorfer, P., & Saad, G. (2005). Managing disruption risks in supply chains. *Production and Operations Management*, 14(1), 53–68.
- Klibi, W., Martel, A., & Guitouni, A. (2010). The design of robust value-creating supply chain networks: A critical review. *European Journal of Operational Research*, 203(2), 283–293.
- Kochen, M. (1975). Applications of fuzzy sets in psychology. *Fuzzy sets and their applications to cognitive and decision processes* (pp. 395–408). Academic Press.
- Krejci, J., & Ishizaka, A. (2018). FAHPSort: A fuzzy extension of the AHPSort method. *International Journal of Information Technology & Decision Making*, 17(4), 1119–1145.
- Kumar, S., & Chandra, C. (2010). Supply chain disruption by avian flu pandemic for US companies: A case study. *Transportation Journal*, 49(4), 61–73.
- Kwon, D. (2019). Demand uncertainty, cost behavior, and the Asian financial crisis: Evidence from Korea. *Sustainability*, 11(8), 2238.
- Li, Y., Zhen, X., Qi, X., & Cai, G. G. (2016). Penalty and financial assistance in a supply chain with supply disruption. *Omega*, 61, 167–181.

- Lin, Y., & Zhou, L. (2011). The impacts of product design changes on supply chain risk: A case study. *International Journal of Physical Distribution & Logistics Management*, 41(2), 162–186.
- Loh, H., & Van Thai, V. (2015). Cost consequences of a port-related supply chain disruption. *The Asian Journal of Shipping and Logistics*, 31(3), 319–340.
- Lolli, F., Ishizaka, A., Gamberini, R., Rimini, B., & Messori, M. (2015). FlowSort-GDSS—A novel group multi-criteria decision support system for sorting problems with application to FMEA. *Expert Systems with Applications*, 42(17–18), 6342–6349.
- Mahajan, K., & Tomar, S. (2021). COVID-19 and supply chain disruption: Evidence from food markets in India. *American Journal of Agricultural Economics*, 103(1), 35–52.
- Manners-Bell, J. (2014). *Supply chain risk: Understanding emerging threats to global supply chains*. Kogan Page.
- Mardani, A., Zavadskas, E., Govindan, K., Amat Senin, A., & Jusoh, A. (2016). VIKOR technique: A systematic review of the state of the art literature on methodologies and applications. *Sustainability*, 8(1), 37.
- Memon, N. (2016). Fast food: 2nd largest industry in Pakistan. *Pakistan Food Journal*, 3(1), 1–3.
- Mohan, U., Viswanadham, N., & Trikha, P. (2009). Impact of Avian Influenza in the Indian poultry industry: A supply chain risk perspective. *International Journal of Logistics Systems and Management*, 5(1–2), 89–105.
- Mousseau, V., & Slowinski, R. (1998). Inferring an ELECTRE TRI model from assignment examples. *Journal of Global Optimization*, 12(2), 157–174.
- Nakat, Z., & Bou-Mitri, C. (2021). COVID-19 and the food industry: Readiness assessment. *Food Control*, 121, 107661.
- Obayelu, A., Edewor, S., & Ogbe, A. (2020). Trade effects, policy responses and opportunities of COVID-19 outbreak in Africa. *Journal of Chinese Economic and Foreign Trade Studies*, 14(1), 44–59.
- Oke, A., & Gopalakrishnan, M. (2009). Managing disruptions in supply chains: A case study of a retail supply chain. *International Journal of Production Economics*, 118(1), 168–174.
- Park, Y., Hong, P., & Roh, J. (2013). Supply chain lessons from the catastrophic natural disaster in Japan. *Business Horizons*, 56(1), 75–85.
- Peng, M., Peng, Y., & Chen, H. (2014). Post-seismic supply chain risk management: A system dynamics disruption analysis approach for inventory and logistics planning. *Computers & Operations Research*, 42, 14–24.
- Runkler, T. (1997). Selection of appropriate defuzzification methods using application specific properties. *IEEE Transactions on Fuzzy Systems*, 5(1), 72–79.
- Sarkis, J., Cohen, M., Dewick, P., & Schroder, P. (2020). A brave new world: Lessons from the COVID-19 pandemic for transitioning to sustainable supply and production. *Resources, Conservation, and Recycling*, 159, 1–4.
- Schmitt, A., Sun, S., Snyder, L., & Shen, Z. (2015). Centralization versus decentralization: Risk pooling, risk diversification, and supply chain disruptions. *Omega*, 52, 201–212.
- Shu, T., Chen, S., Wang, S., & Lai, K. (2014). GBOM-oriented management of production disruption risk and optimization of supply chain construction. *Expert Systems with Applications*, 41(1), 59–68.
- Simon, J., & Omar, A. (2020). Cybersecurity investments in the supply chain: Coordination and a strategic attacker. *European Journal of Operational Research*, 282(1), 161–171.
- Singh, S., Kumar, R., Panchal, R., & Tiwari, M. (2021). Impact of COVID-19 on logistics systems and disruptions in food supply chain. *International Journal of Production Research*, 59(7), 1993–2008.
- Thun, J., & Hoenig, D. (2011). An empirical analysis of supply chain risk management in the German automotive industry. *International Journal of Production Economics*, 131(1), 242–249.
- Tokui, J., Kawasaki, K., & Miyagawa, T. (2017). The economic impact of supply chain disruptions from the Great East-Japan earthquake. *Japan and the World Economy*, 41, 59–70.
- Wang, W., Tang, J., & Wei, F. (2020). Updated understanding of the outbreak of 2019 novel coronavirus (2019-nCoV) in Wuhan, China. *Journal of Medical Virology*, 92(4), 441–447.
- Warren, M., & Hutchinson, W. (2000a). Cyber attacks against supply chain management systems: A short note. *International Journal of Physical Distribution & Logistics Management*, 30(7/8), 710–716.
- Warren, M., & Hutchinson, W. (2000b). Cyber attacks against supply chain management systems: A short note. *International Journal of Physical Distribution & Logistics Management*, 30(7/8), 710–716.
- Workie, E., Mackolil, J., Nyika, J., & Ramadas, S. (2020). Deciphering the impact of COVID-19 pandemic on food security, agriculture, and livelihoods: A review of the evidence from developing countries. *Current Research in Environmental Sustainability*, 2, 100014.
- Xie, C., Anumba, C., Lee, T., & Schoenherr, T. (2011). Assessing and managing risks using the supply chain risk management process (SCRMP). *Supply Chain Management: An International Journal*, 16(6), 474–483.

- Yang, J., Qi, X., & Yu, G. (2005). Disruption management in production planning. *Naval Research Logistics (NRL)*, 52(5), 420–442.
- Yang, Y. (2011). Risk management of Taiwan's maritime supply chain security. *Safety Science*, 49(3), 382–393.
- Yu, W. (1992). ELECTRE TRI(aspects méthodologiques et manuel d'utilisation). Université de Paris-Dauphine, LAMSADE, Paris.
- Zhang, Y., Wei, K., Shen, Z., Bai, X., Lu, X., & Soares, C. (2020). Economic impact of typhoon-induced wind disasters on port operations: A case study of ports in China. *International Journal of Disaster Risk Reduction*, 50, 101719.
- Zighan, S. (2021). Managing the great bullwhip effects caused by COVID-19. *Journal of Global Operations and Strategic Sourcing*, 28(1), 28–47.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.