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The logistics service providers during the COVID-19 pandemic: The prominence and the cause-effect structure of uncertainties and risks

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A R T I C L E I N F O

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A B S T R A C T

Uncertainties and risks play a central role in creating vulnerabilities for logistics service operations. Over the years, Logistic Service Providers (LSPs) have learned how to ensure resilience to confront uncertainties and risks triggered by adverse events. However, quite unlike any seen in recent times, the COVID-19 pandemic brings about unavoidable uncertainties and risks for the logistics industry. Yet, there is no common approach to contextualize how they interact together. We incorporate an empirical research design and make a threefold contribution: first, we identify uncertainties and risks that LSPs encounter during the COVID-19 pandemic and investigate their prominence. Second, we unveil intertwined schemes of afore-identified uncertainties and risks and augment the understanding of their cause-effect structure. Third, we provide an uncertainty and risk assessment guideline for LSPs affected by threats emerging from unforeseeable crises.

In this study, we combine qualitative work and the fuzzy DEMATEL method. Qualitative thematic analysis of in-depth interviews reveals the most important uncertainties (COVID-19 measures, employee welfare, forecast horizon, demand change, and government regulations) and risks (COVID-19 risk, delivery delays, supply chain disruptions, financial failure, and product returns) for LSPs. The fuzzy DEMATEL method shows that COVID-19 measures and COVID-19 risk are highly prominent and influence other factors. The results indicate that demand change, government regulations, and supply chain disruptions are net causers, and employee welfare, financial failure, forecast horizon, delivery delays, and product returns are net receivers. Distinctly, employee welfare is the most affected factor, empirically confirming that major risks for LSPs are related to the human factor. More investigation in our results suggests that supply chain disruptions and demand change, two factors triggered by the COVID-19 pandemic, influence financial failure and forecast horizon, two factors associated with operational performance.

1. Introduction

The COVID-19 pandemic has wreaked devastation on global social and economic systems. The ramifications of this pandemic, or so-called great shock, have impacted manufacturing processes and worldwide supply chains (Chen, 2020). Globalization accelerates this process of supply chain interdependence and creates difficulties for both individuals and the global supply chain, resulting in many uncertainties and risks on a global scale. Uncertainty and risk are inherent in all economic activities, albeit to varying degrees (Toma et al., 2012). As supply chains become complex, uncertainties and risks become more significant (Choi, 2021; Shahbaz et al., 2019). Turkey's exports fell by 41% in April 2020 due to the inability of LSPs to transport white goods, textiles, cars, and auto parts (Pitel, 2020). The US automakers could not receive parts from Chihuahua (a Mexican state) plants because more than half of the workers were absent (Okamoto, 2020). Supply chains are exposed to unprecedented supply chain disruptions (Ivanov & Das, 2020), uncertainties (P. Sharma et al., 2020), and risks (R. Sharma et al., 2020) during the COVID-19 pandemic.

Uncertainty and risk are important research topics, and many papers investigate these concepts in the literature (e.g., Fan & Stevenson, 2018; Prakash et al., 2017; Simangunsong et al., 2012). However, there is no

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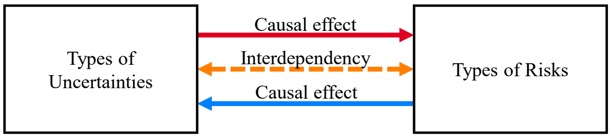

Fig. 1. The components under examination.

coherence in the literature about how uncertainty and risk are conceptualized. Even though numerous studies have been conducted on the classifications of uncertainty (Sanchez-Rodrigues et al., 2008) and risk (Tarei et al., 2018), there is a dearth of empirical research examining multiple types of uncertainties and risks simultaneously (Choi et al., 2019). Even though uncertainty consists of multi-dimensions, it is usually considered a single dimension, namely the environmental dimension (Yu et al., 2017), resulting in a poor understanding of the environment (P. Sharma et al., 2020). Nonetheless, a limited number of studies on various types of uncertainties and risks in conjunction with cause-effect interactions exist in the literature. In business activities, situations that are overlooked or not initially considered may arise, and these unforeseen events can create uncertainty, which can be a source of risk (Toma et al., 2012). Defining and classifying risks enable companies to proactively manage uncertainties that may arise in the future (Hallikas et al., 2004). There is a symbiotic relationship between uncertainties and risks, a field that requires additional research.

There is a need to clarify the prominence and cause-effect relationships of uncertainties and risks that significantly impact the logistics industry. Prioritizing the uncertainties and risks and structuring their cause-effect relationships will contribute to understanding the business environment and enable companies to effectively allocate essential resources, develop employee welfare strategies to avoid workflow disruptions, ensure flexibility, and reorganize distribution against demand fluctuations and supply chain disruptions. The purpose of this study is to identify uncertainties and risks that LSPs encounter during the COVID-19 pandemic and investigate their prominence and cause-effect structure. This study reveals uncertainties and risks in the logistics industry by conducting in-depth interviews and thematic analysis and explores their cause-effect structure by employing the fuzzy DEMATEL (Decision Making Trial and Evaluation Laboratory) method. Fig. 1 summarizes the basis of this research work. The solid lines in the model represent one-way causal effect relationships, while the dotted line symbolizes interdependencies among uncertainties and risks.

This paper is organized as follows. Section 2 presents the literature for uncertainty and risk. Section 3 describes the methodological framework of in-depth interviews, thematic analysis, and the fuzzy DEMATEL method and its corresponding algorithm. Section 4 exhibits the results and the sensitivity analysis. Section 5 addresses the theoretical and managerial implications. Sections 6 and 7 demonstrate conclusions and discussion and limitations and directions for future research, respectively.

2. Literature review

While more recent attention focuses on the uncertainty and risk subjects in several research domains, a large and growing body of literature investigates the uncertainty and risk issues concerning the logistics industry. Various studies (Prakash et al., 2017; Wang et al., 2019, 2014) consider uncertainty and risk as similar concepts due to their being indivisible and their simultaneous management in practice (Wang, 2018), whereas other studies (Sachs, 2018; Shahbaz et al., 2019; Simangunsong et al., 2012; Stewart, 2021) describe uncertainty and risk as different concepts. Essentially, the uncertainty may have negative and positive consequences, whereas the risk is solely related to negative results (Simangunsong et al., 2012). This section discusses the literature of uncertainty and risk concepts and reveals the types of uncertainties and risks.

Table 1
Comparison of similar studies.

Study	Uncertainty	Risk	Method	Domain of application
Bae (2012)	X		Support-vector machines	Logistics industry
Lin et al. (2013)	X		Principle-agent modeling	Logistics service industry
Kazemi Zanjani and Nourelfath (2014)	X		Stochastic modeling	Service industry
Liu and Wang (2015)		X	Quality control game model	Logistics service industry
Liu et al. (2015)	X		Scheduling model	Logistics service industry
Govindan and Chaudhuri (2016)		X	DEMATEL	Logistics service industry
Moslemi et al. (2016)		X	Case study	Logistics industry
Baharmand et al. (2017)		X	Qualitative content analysis & field survey	Logistics industry
Multaharju et al. (2017)		X	Case study	Logistics service industry
Subramanian and Abdulrahman (2017)		X	Structural equation modeling	Logistics industry
Avelar-Sosa et al. (2018)		X	Structural equation modeling	Logistics service industry
This study	X	X	Qualitative thematic analysis & fuzzy DEMATEL	Logistics service industry

The existing literature particularly focuses on the multidimensionality of uncertainties and risks (Stewart, 2021). More frequently, studies concentrating on uncertainty or risk regarding the logistics industry adopt structural equation modeling or a case study approach. A few studies investigate relationships among logistics risks or uncertainties; however, none examine these two subjects simultaneously. The nature of how uncertainties and risks interact concerning the logistics service domain remains unclear. Table 1 compares similar studies and addresses the literature gap.

After briefly reviewing the literature on uncertainty and risk concepts, this section outlines the several types of uncertainties and risks. Then, the prominence of uncertainties and risks and their cause-and-effect structure are examined.

2.1. Uncertainty

Uncertainty exists when there are several possible outcomes, some or all of which are unknown, and the probability of each cannot be calculated (Stewart, 2021). Uncertainty arises when it is impossible to predict an outcome's likelihood and the consequences of a decision (Sanchez-Rodrigues et al., 2010b). Uncertainty stems from the variability resulting from the changes in nature, social environment, and technology and limited knowledge due to the lack of observations and measurements and unreachable information (Wattanakul et al., 2019). Uncertainty limits managers' decision-making capabilities by preventing them from determining the variances and probability of occurrences (Christopher & Lee, 2004; Wang, 2018). However, this does not mean that uncertainty is always detrimental to businesses; it is associated with positive and negative outcomes. For instance, profit increases or decreases when demand uncertainty exceeds or falls short of expectations (Simangunsong et al., 2012).

Uncertainty may stem from a variety of sources. For example,

Table 2
Taxonomy of logistics uncertainty types.

Reference	Supply uncertainty	Demand uncertainty	Internal uncertainty	External uncertainty
Kamrad and Lele (1998)			Process	Market (changes in the price of the output)
Christopher and Lee (2004)	Shipper Provider	Customer		Trade body Policymaker/influencer
Sawhney (2006)	Supplier	Customer	Process	
Sanchez-Rodrigues et al. (2010b)	Shipper Forecasting and ordering products Raw material sourcing Production processes Loading delays	The receiver of products Any delivery restrictions imposed by the customer	Inefficiency originated by the carrier (e.g., vehicle breakdown or insufficient drivers)	Disturbance (unplanned road congestion and changes in fuel prices)
Bae (2012)				Environmental
Simangunsong et al. (2012)	Supplier Forecast horizon Parallel interaction	End-customer demand Demand amplification	Chain configuration, infrastructure, and facilities	Government regulations, competitor behavior, and macroeconomic issues Natural disasters
Kazemi Zanjani and Nourelfath (2014)	External suppliers' lead time and capacity	Demand		
Liu et al. (2015)			Operation time	
Prakash et al. (2017)	Supply chain	Demand		
Wang (2018)		Demand		
Wang et al. (2019)		Demand		
Wattanakul et al. (2019)		Demand	Operational (shipment schedule and cost)	Severe risk/economic pressure (terrorism or natural disaster)
P. Sharma et al. (2020)	Supply chain	Demand		Uncertainties related to COVID-19
This study	Forecast horizon	Demand change	Employee welfare	Government regulations COVID-19 measures

uncertainty is caused by the supplier, carrier, customer, control systems, and other external variables (Sanchez-Rodrigues et al., 2008). In other words, uncertainty can be traced throughout the supply chain, whether on the ship, in the port, or during transit (Wattanakul et al., 2019). We classify LSPs' uncertainties into four categories: supply, demand, internal, and external uncertainty (see Table 2). Supply uncertainty includes uncertainties related to the forecast horizon, shipper, provider, production, and supply chain process. Demand uncertainty is related to the customer or receiver of the products. Internal uncertainties are related to the process and the operations and include inefficiencies originated by the carrier. External uncertainties arise due to the environment, government regulations, competitor behavior, macroeconomic concerns, natural disasters, and pandemics such as COVID-19.

2.2. Risk

Risk is an event's probability of occurrence and adverse consequences (Calatayud et al., 2017). The greater the impact of the threat on the supply chain, the greater the risk is, even if it is less likely to occur (Sanchez-Rodrigues et al., 2010b). The risk is a threat that interrupts regular activities and end planned operations (Wang et al., 2020) which may negatively affect credibility, reputation, and trust (Fan & Stevenson, 2018). There are various types of risk classification in the supply chain management domain, and more specifically in the logistics sector. Types of risks in a supply chain are logistics, information, and financial risks (Shahbaz et al., 2019), customer-side, company-side, and environment-side (Wang et al., 2015). According to Baharmand et al. (2017), logistics risks include delivery delays, market fluctuations, insufficient capacity, cargo loss and decay, unreliable information, and ethical problems.

We classify LSPs' risks into four categories: supply, demand, internal, and external risk (see Table 3). Supply risks are related to supplier performance (e.g., supply chain disruptions, the bankruptcy of suppliers, delays in supply lead-time, short supplies, outsourcing, and control), products (e.g., poor quality of supplies), or process (e.g., disruption in production, low production capability, inflexibility in capacity, low production yield, wrong order quantities, process risks related to value-added activities, property damage, low capacity). Demand risks are customer-related issues such as fluctuations in demand, seasonality, volatile customers, change in customer preference, inaccurate forecasting of demand, payment failure, and fraud. Internal risks are financial failure (e.g., cash flow issues, intellectual property, merger/alliance, and trust), delivery delays, leadership and management style (e.g., ethical concerns, market perceptions), collaborations, buyer and supplier relationships, sustainability, information flow, IT system failure, loss or damage of cargo, unavailability of necessary vehicles, improper loading, and mode of transport errors. External risks include force majeure such as COVID-19 pandemic, natural and man-made disasters, market fluctuations, economic crisis, and political, social, and industrial issues.

2.3. The prominence and the cause-effect structure of the uncertainties and the risks

The prominence of uncertainties and risks is vital for the allocation of resources. According to Nguyen et al. (2021), physical flow is the primary source of high-ranking risks with potentially serious consequences (e.g., piracy, dangerous cargo, and maritime accidents), whereas informational, financial, and operational issues (e.g., fuel costs) are more uncertain.

Uncertainty generates (Choi et al., 2019) and amplifies (Christopher & Lee, 2004) risk, increases the probability of risk (Wang, 2018), and results in a more complex supply chain (Christopher & Lee, 2004). For instance, supply uncertainty arising from contractual obligations regarding volume or mix delays the scheduled delivery and increases the delivery risk (Sreedevi & Saranga, 2017). The uncertainties related to inventory holding costs and shipment frequency create more risk than volume changes and freight rates (Christopher & Lee, 2004). Supply and demand-side uncertainties can also create supply chain disruptions and logistics risks (Choi et al., 2019). More specifically, road network congestion, an external uncertainty, is one of the primary reasons for the delivery delays, an internal risk. Volatile demand, a demand risk, occurs due to unexpected promotions (Sanchez-Rodrigues et al., 2010a), an internal uncertainty. Uncertainty becomes a cause of risk when it is based on incomplete information or derived from sources that are frequently incompatible with the actual state of a business or competitive market (Toma et al., 2012). On the contrary to popular belief, risks are not only stem from uncertainties; simultaneously, they increase the

Table 3
Taxonomy of logistics risk types.

Reference	Supply risk	Demand risk	Internal risk	External risk
Punniyamoorthy et al. (2013)	Poor quality of supplies Short supplies Delays in supply lead-time Bankruptcy of suppliers Disruption in production Low production capability Inflexibility in capacity	Unanticipated or volatile customer Significant forecast error in demand Receivable risks Change in customer preference Reputation risk	Information risks Wrong choice of transportation mode Damages due to accidents or improper stocking Unavailability of special vehicles Frequent delays in delivery	Policy uncertainty Macroeconomic uncertainty Uncertainty due to government laws and regulations Social uncertainty Nonavailability of skilled workforce Force majeure
Govindan and Chaudhuri (2016)			Buyer and supplier relationship risks	
König and Spinler (2016)	Bankruptcy of suppliers Low production yield Wrong order quantities	Seasonality New product adaptions The volatile customer	Failure of IT systems Delayed deliveries	Terrorist attracts Labor strikes Socio-political crises Force majeure
Moslemi et al. (2016)				Industry risk
Baharmand et al. (2017)			Ethical concerns Information risks Loss of cargo Cargo decay Insufficient capacity Delayed deliveries	Market fluctuations
Calatayud et al. (2017)			Disruptions in the flow of goods Lack of transport services	Failure of critical infrastructure Labor conflicts (e.g., strikes) National threats
Multaharju et al. (2017)			Sustainability-related risks	
Prakash et al. (2017)	Outsourcing that causes supply problems Control risk in supply chain variables Process risks related to value-added activities	Fluctuations in demand Inaccurate forecasting		Natural disasters Economic downturns Terrorism
Sreedevi and Saranga (2017)	Process risks		Delivery risks	
Gouda and Saranga (2018)	Actual supply chain risks			
Jajja et al. (2018)	Supply risks Process risks		Delivery risks	
Tarei et al. (2018)	Crude supply Property damage Low capacity	Fluctuations in demand Inaccurate forecasting Poor prediction of customer demand The volatile customer Payment failure risk Fraud risk	Failure of IT systems Merger/alliance Intellectual property trust Leadership and management style Delayed deliveries	Natural disasters Man-made disasters Legal/political risks Economic crisis Transportation accidents Vandalism during transportation Threats from competitors
Ramesh et al. (2019)	Supplier performance risks Suppliers' supply management Product-related risks Previous supplier score Product-related risk		Buyer-supplier relationship risks Organizational issues Market perception Cash flow issues Network-related risks	Natural disasters Man-made disasters Legal/political risks Economic crisis
Shahbaz et al. (2019)	Supply risks Process risks	Demand risks	Collaboration risks Financial risks Logistics risks	Environmental risks
Wang et al. (2020)	Manufacturing risks	Customer risks		Environmental risks
This study	Supply chain disruptions	Product returns	Financial failure Delivery delays	COVID-19 risk

possibility of uncertainty in the supply chains (Sanchez-Rodrigues et al., 2010a). Risks contribute to uncertainty in a complex environment such as logistics (Calatayud et al., 2017). Internal risks such as ineffective information flow or coordination between marketing and logistics departments create uncertainty (Sanchez-Rodrigues et al., 2010a). Global supply chain risks (e.g., inadequate departmental coordination) and supply and demand risks (e.g., mismatching supply and demand with insufficient buffer stock) (Stewart, 2021) may cause uncertainty in the supply chain. A strong interdependence exists between uncertainty and risk (Jedynak & Bąk, 2020), necessitating a collaborative action (Hallikas et al., 2004).

Systems theory conceptualizes an organization as a network of interconnected systems, a "system of systems" (SoS), which guides in understanding the risks as constitutionally intertwined (Fan & Stevenson, 2018). For example, supply disruptions, a supply risk, and operational problems in unloading and loading, an internal risk, results in delivery delays, another internal risk; volatile demand, a demand risk, may occur due to, and changes in customer preferences, another demand risk (Sanchez-Rodrigues et al., 2010a). Along with risks, uncertainties are a critical part of this SoS approach (Hou & Zhao, 2020). For instance, supply uncertainty is related to demand uncertainty. Thus, one can argue that uncertainties are intertwined like risks.

The SoS approach regarding uncertainty also urges the LSP managers to set strategies to mitigate risk (Hou & Zhao, 2020). Risk management in logistics is challenging because of the complicated and fragile environment shaped by uncertainties (Shahbaz et al., 2019). In this sense, managers can take additional precautions when they are aware of these intertwined relationships rather than treating uncertainties and risks independently. Risks and uncertainties identified, evaluated, and compared may require joint action or be incorporated into planning processes (Hallikas et al., 2004).

However, LSPs are still unclear about the types of uncertainties and

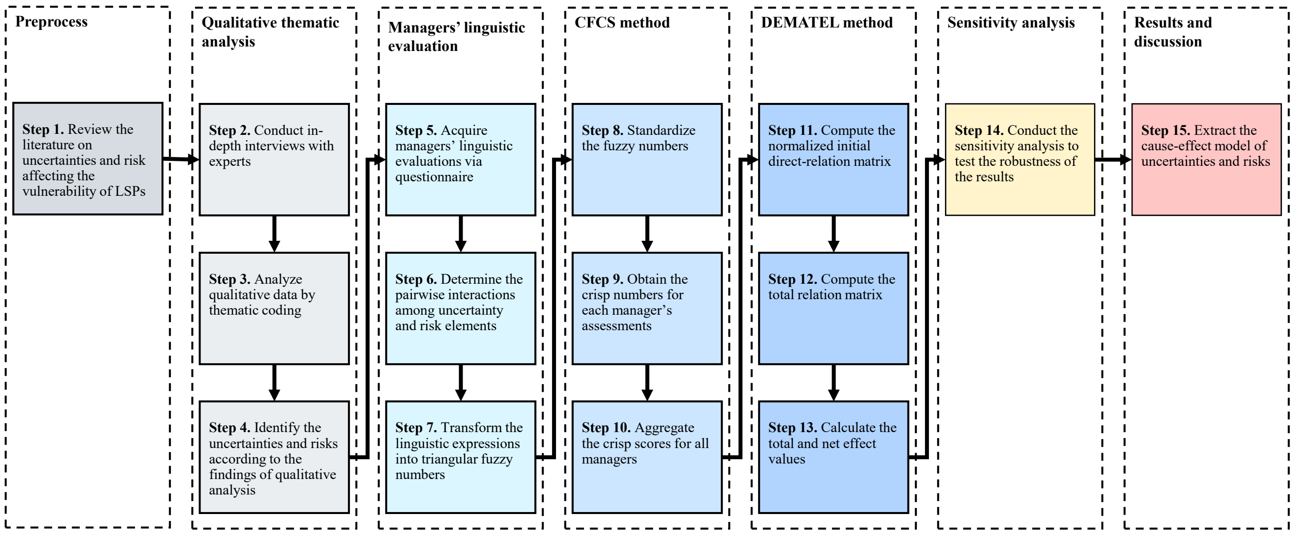

Fig. 2. Flowchart of the proposed method's stages.

risks and their interaction during the COVID-19 pandemic. Thus, this symbiotic relationship among uncertainties and risks necessitates further research to understand their underlying cause-effect structure. Understanding the prominence of uncertainties and risks and their causal relationship enables LSPs to diagnose their vulnerabilities. Accordingly, this study proposes three research questions:

RQ1. What are the uncertainties and risks encountered by the LSPs during the COVID-19 pandemic?
RQ2. How prominent the determined uncertainties and risks are for LSPs during the COVID-19 pandemic?
RQ3. What is the cause-effect structure of these uncertainties and risks?

3. Methodology

This study's methodology introduces a literature review to identify the relevant uncertainties and risks encountered by the LSPs during the COVID-19 pandemic. In-depth interviews with experts follow this to specify primary uncertainties and risks. Then we analyze the data collected from managers of LSPs using a fuzzy DEMATEL method to explain the complex causal structure and interdependencies among these uncertainties and risks.

Fig. 2 illustrates the research's flowchart to analyze and prioritize the significant uncertainties and risks for LSPs during the COVID-19 pandemic. The research plan consists of six stages: (1) identifying the uncertainties and risks by reviewing the literature and conducting in-depth interviews with experts and specifying the uncertainties and risks and the questionnaire design, (2) linguistic data collection via conducting the questionnaire with managers of LSPs and construct results by triangular fuzzy numbers, (3) defuzzificating triangular fuzzy numbers by the CFCS method, (4) data analysis by employing the fuzzy DEMATEL method, (5) conducting the sensitivity analysis to test the robustness of the managers' evaluations, and (6) presenting the overall prominence and causal effect diagram and the conclusion.

3.1. In-depth interviews and qualitative analysis

Since the uncertainty and risk elements presented in Section 2 are based on the general logistics service domain, it is not valid to make direct inferences for the specific conditions of the COVID-19 pandemic. However, the uncertainty and risk elements identified by reviewing the literature provide a starting point for the following in-depth interviews used to identify uncertainty and risk elements typical to the logistics

Table 4
In-depth interview experts' profiles.

No.	Position/ Role	Branch	Experience (years)	Knowledge, skills, and competences	Interview duration (minutes)
E1	Professor	Logistics management	19	Logistics system design, supply chain analysis, and sustainability	46
E2	Professor	Supply chain management	22	Lean manufacturing, logistics, supply chain management, and sustainability	69
E3	Executive	Logistics services	21	Transportation management and integrated supply chain solutions	54
E4	Executive	Logistics services	24	Sustainable logistics services and integrated supply chain solutions	57
E5	Professor	Logistics management	27	Warehouse management and supplier relationship management	42
E6	Executive	Logistics services	20	Foreign trade management and procurement management	53

service industry conditions shaped by the COVID-19 pandemic. Qualitative research is preferred when the research subject is relatively unexplored since it is more eligible to elicit new information and support phenomenological validity (Vanderstoep & Johnson, 2009). In particular, in-depth interviews, a qualitative data collection technique, allow conceptualizing a phenomenon by capturing contextual information (Trochim & Donnelly, 2006). Following the literature review, we interviewed experts to capture their opinions to identify the most significant uncertainty and risk factors for the LSPs working in the COVID-19 environment. We employ in-depth interviews based on the procedure

Table 5
Uncertainty and risk themes identified at the initial scanning stage of thematic analysis.

Uncertainty/Risk theme	Category	Subcategory	Element number	Theme code
Forecast horizon	Uncertainty	Supply	1	US1
Suppliers' operational uncertainties (e.g., equipment, labor)	Uncertainty	Supply	2	US2
Employee welfare	Uncertainty	Internal	1	UI1
Uncertainties about vehicles, drivers, and delivery staff	Uncertainty	Internal	2	UI2
Operational time and costs	Uncertainty	Internal	3	UI3
The volatility of fuel prices	Uncertainty	External	1	UE1
Government regulations	Uncertainty	External	2	UE2
Competitive environment	Uncertainty	External	3	UE3
Macroeconomic fluctuations (e.g., exchange or interest rates)	Uncertainty	External	4	UE4
Uncertainties about customs and borders	Uncertainty	External	5	UE5
COVID-19 measures	Uncertainty	External	6	UE6
Demand change	Uncertainty	Demand	1	UD1
Delay in supply lead-time	Risk	Supply	1	RS1
Product-related risks (e.g., materials used, quality, durability)	Risk	Supply	2	RS2
Bankruptcy of suppliers	Risk	Supply	3	RS3
Dependency to a single supplier	Risk	Supply	4	RS4
Supply chain disruptions	Risk	Supply	5	RS5
Product recalls	Risk	Supply	6	RS6
Financial failure	Risk	Internal	1	RI1
IT & control/tracking systems failure	Risk	Internal	2	RI2
Road accidents	Risk	Internal	3	RI3
Logistics safety (e.g., safe movement of people and goods)	Risk	Internal	4	RI4
Delivery delays	Risk	Internal	5	RI5
Improper handling, packaging, loading, and shipping	Risk	Internal	6	RI6
Damage and loss	Risk	Internal	7	RI7
Cyber-security	Risk	Internal	8	RI8
Transportation infrastructure unavailability	Risk	External	1	RE1
Civil unrest	Risk	External	2	RE2
Adverse weather conditions	Risk	External	3	RE3
Natural disasters	Risk	External	4	RE4
Regional conflicts	Risk	External	5	RE5
Law enforcement's intervention	Risk	External	6	RE6
Decrease of human mobility	Risk	External	7	RE7
COVID-19 risk	Risk	External	8	RE8
Product returns	Risk	Demand	1	RD1
Payment failure	Risk	Demand	2	RD2

used by Verkooij and Spruit (2013). The expert selection protocol is based upon two criteria. First, experts should have broad experience and practical knowledge in the logistics services industry. Second, they should be actively involved in logistics service operations or research. Having this up-to-date knowledge and experience would allow experts to make sound judgments on the uncertainties and risks that affect the vulnerability of LSPs during the COVID-19 pandemic. Accordingly, we determine a sample of three academics and three executives with over fifteen years of experience in logistics services. Table 4 lists the six experts interviewed in this study who are adhered to the defined selection criteria.

During the in-depth interviews, the interviewees are asked to clarify the most significant drivers affecting LSPs' operations within the scope of the COVID-19 pandemic. Follow-up questions explore the predictability and eventuality of these drivers to support classifying themes as uncertainty or risk. The in-depth interviews are tape-recorded and transcribed. The transcript summaries are verified by the interviewees. Then, the interviews are analyzed using thematic coding and compared to and associated with the reviewed uncertainty and risk typology by grouping closely related narratives concerning the uncertainty and risk themes.

The thematic coding is performed by adapting the conceptual framework proposed by Flick (2018). A three-digit coding procedure is followed for the coding process of the qualitative data. Apriori codes are employed to reflect categories complying with the literature review (Gibson & Brown, 2009). As reviewed and classified in Section 2, the literature on uncertainty emphasizes supply, demand, internal, and external uncertainties, and the risk literature focuses on supply, demand, internal, and external risks. The first digit of the code classifies a theme as uncertainty (U) or risk (R), the second digit signifies uncertainty or risk subcategory (S = Supply, D = Demand, I = Internal, E = External), and the third digit designates the element number (e.g., 1, 2, 3, 4). The thematic coding process is held in two stages. At the initial scanning stage, twelve uncertainty themes and twenty-four risk themes are identified. At the elimination stage, these are reduced to five for each theme. As a threshold procedure, a minimum of three experts' (half of the sample group) narratives is needed to refer to reasonable consideration of defining a theme within the uncertainty and risk framework. The rationale for this approach is that the themes would exclude highly specific narratives but keep enough details to distinguish various uncertainty and risk elements. Table 5 exhibits the identified uncertainty and risk themes at the initial scanning stage and the qualitative analysis coding system.

Three executives expressed concern for employee welfare during the interviews, while three interviewees (one professor and two executives) expressed concern about the product returns. Employee welfare is an underestimated area of research, and there are limited studies that consider employees as a part of uncertainty and risk and do not separate uncertainty from risk. For example, Wang et al. (2015, 2018) identify inadequate communication between the company and its drivers as an internal uncertainty and risk, while labor/driver shortage is classified as an environmental uncertainty and risk. Sanchez-Rodrigues et al. (2010b) consider employee-related issues under uncertainty and state how driver inadequacy contributes to the internal uncertainty related to the carriers. In this perspective, businesses view uncertainties and risks associated with employees primarily through the lens of inefficiency, communication, and scarcity. In this study, employee welfare is defined as an internal uncertainty since it cannot be predicted and is expected to have positive or negative results. There is no mention of product returns in the literature on uncertainty and risk. However, the product returns literature acknowledges returns as a risk for businesses (Padmanabhan & Png, 1997). Padmanabhan and Png (1997) consider returns policies a risk-sharing mechanism in the business-to-business (B2B). Fu et al. (2016) identify an imbalanced distribution of consumers' product-return biases and develop a model for identifying the riskiest product returns (i.e., most probable to return or not). Rao et al. (2014) analyze the impact of physical distribution services in product returns and find that managing expected delivery timeliness and delivery reliability and maintaining delivery promises reduces the risk of product returns. Martino et al. (2015) mention the product return risk related to the quality check in the central warehouse or logistic center and post-season unsold goods. According to the interviews and literature, this study considers product returns to be a demand risk. Thus, examining employee welfare and product returns in the context of LSPs is a rare field of research that contributes to the literature on uncertainty and risk.

Table 6
Uncertainties and risks specified by the in-depth interviews.

Denotation	Item	Description	Reference
UR_1	Demand change	Variation in quantity, timing, specifications, delivery, and preferences	Avelar-Sosa et al. (2018), Kazemi Zanjani and Nourelfath (2014)
UR_2	Government regulations	Imposition of prohibitions and restrictions by state administrations	Multaharju et al. (2017), Simangunsong et al. (2012)
UR_3	COVID-19 measures	Preventative actions taken in response to the COVID-19	P. Sharma et al. (2020)
UR_4	Employee welfare	Quality of health, well-being, and happiness of the employees	Kekkonen et al. (2018)
UR_5	Forecast horizon	The period for which LSPs can predict the future	Liu et al. (2015), Simangunsong et al. (2012)
UR_6	Delivery delays	Delay in order processing, shipping, or delivery	Baharmand et al. (2017)
UR_7	Financial failure	Disruptions in the payments and remittance or sudden default or bankruptcy	Hwang and Kim (2018), R. Sharma et al. (2020)
UR_8	Product returns	Rejections or returns of goods	Martino et al. (2015), Robertson et al. (2020), Yalabik et al. (2005)
UR_9	Supply chain disruptions	Disruptions in the production and the flow of goods	Choi (2021), Choi et al. (2016)
UR_{10}	COVID-19 risk	Health complications associated with the COVID-19	R. Sharma et al. (2020)

We identified five uncertainty and five risk elements through the elimination stage of thematic analysis. Uncertainty factors are forecast horizon (a supply uncertainty), demand change (a demand uncertainty), employee welfare (an internal uncertainty), government regulations (an external uncertainty), and COVID-19 measures (an external uncertainty), and risk factors are supply chain disruptions (a supply risk), product returns (a demand risk), financial failure (an internal risk), delivery delays (an internal risk), and COVID-19 risk (an external risk). Table 6 presents the items retained after the thematic analysis of the qualitative data. Accordingly, we reorganize identified uncertainties and risks and conceptualize them in conformity with the literature.

3.2. Sampling process and quantitative data collection

Following the expert interviews, we surveyed managers of fifteen LSPs operating in Turkey to elicit the cause-effect relations and interdependencies among uncertainties and risks. For data collection, the expert sampling method is employed, which is a subcategory of purposive sampling. Purposive sampling involves selecting the sampling units related to the most information on the specific subject (Guarte & Barrios, 2006). Expert sampling suggests collecting data from a sample of people known for their experience and expertise in the field (Trochim & Donnelly, 2006). Firstly, we identify companies engaged in activities in the logistics service industry for more than five years. Then, we contact the managers of these LSP companies, who have experience in logistics service operations for more than five years, to capture their opinions on the uncertainties and risks for LSPs during the COVID-19 pandemic. A questionnaire is used to obtain the managers' evaluations on the pairwise interactions among uncertainty and risk elements specified by the in-depth interviews. Respondents are also asked about the company's activity branch, age, size, position, and experience. It takes from 45 to 60 min for one respondent to complete the questionnaire. Table 7 lists the fifteen managers surveyed in this study.

The questionnaire is composed of four parts. The first part describes each uncertainty and risk to make it clear for responding. In the second part, respondents are asked to rate the significance of each uncertainty and risk using a five-point Likert scale. The ratings of "1, 2, 3, 4, and 5" represent "not at all important", "slightly important", "moderately important", "very important", and "extremely important", respectively. The third part is a five-point Likert scale pairwise association matrix to assess the influence of uncertainties and risks on each other. The ratings of "0, 1, 2, 3, and 4" represent "no influence", "very low influence", "low influence", "high influence", and "very high influence", respectively. Finally, the fourth part covers organizational demographics.

3.3. Prioritizing the uncertainties and risks for LSPs with the fuzzy DEMATEL method

In this study, we use the fuzzy DEMATEL method to determine the prominent uncertainty and risk factors that affect the vulnerability of LSPs under overwhelming COVID-19 conditions and evaluate their cause-effect structure. We consider these factors as interrelated elements, reflecting that various uncertainties and risks influence each other. The rationale for selecting the DEMATEL method is its methodological advantage over other decision-making methods to handle complex causal relationships and interdependencies (Si et al., 2018).

Table 7
Questionnaire respondents' profiles.

No.	Position/Role	Experience (years)	Company age (years)	Company size (number of employees)	Company activity branch
M1	Traffic manager	20	52	500 to 999	Third-party logistics, transportation, warehousing
M2	Regional director	23	113	1000 or more	Courier shipment, transportation, warehousing
M3	Warehouse manager	21	23	250 to 499	Courier shipment
M4	CEO	14	33	500 to 999	Courier shipment
M5	General director	11	28	50 to 249	Warehousing
M6	Director of E-commerce	20	78	1000 or more	Plant logistics, third-party logistics, transportation management systems, warehousing
M7	Logistics manager	21	35	500 to 999	Plant logistics, transportation
M8	Team leader	15	60	1000 or more	Plant logistics, transportation, transportation management systems, warehousing
M9	Board chairman	13	13	1 to 50	Transportation, transportation management systems
M10	Direct sales manager	19	57	500 to 999	Transportation, transportation management systems
M11	Team leader	16	32	500 to 999	Plant logistics, transportation, transportation management systems, warehousing
M12	Regional director	12	26	250 to 499	Transportation, transportation management systems, warehousing
M13	Logistics manager	21	21	50 to 249	Transportation
M14	Board member	21	25	250 to 499	Courier shipment, third-party logistics, transportation
M15	Foreign trade manager	22	69	1000 or more	Third-party logistics, transportation, warehousing

The DEMATEL method aims to find integrated solutions for fragmented and antagonistic phenomena (Wu, 2008). It is an enhanced procedure for analyzing and designing a structural model to measure complicated causal relations among multiple criteria (Chang et al., 2011). It features complex cause-effect relationships between a set of elements through matrices (Wu & Lee, 2007). It has a methodological capability to analyze the pairwise interrelations between items (Si et al., 2018). The DEMATEL method presumes that all factors have different levels of effects on each other, i.e., they are not independent (Tzeng & Shen, 2017). Compared with other decision-making methods, the DEMATEL method has the following advantages (Lin & Tzeng, 2009; Liu et al., 2014; Si et al., 2018; Tzeng et al., 2007): (1) it can effectively analyze the direct and indirect effects among different factors and enable the decision-maker to understand the complex causal structure, (2) it can visualize the interrelationships between factors via a cause-effect model, allowing the decision-maker to understand which factors have influences on the others, (3) it can determine the prominence of factors.

In recent years, considering the ambiguity of respondents' opinions, many scholars (e.g., Ocampo et al., 2019; Sathyan et al., 2020; Zhang & Su, 2019; Zhou et al., 2018) combine fuzzy logic techniques with the DEMATEL method to satisfy a solution for the vagueness in these complex problems. We analyze the managers' data with the fuzzy DEMATEL method similar to previous studies (e.g., Addae et al., 2019; Chang et al., 2011; Sathyan et al., 2020; Zhou et al., 2011). The steps of the fuzzy DEMATEL method are explained in the next sections.

3.4. Evaluating the uncertainties and risks for LSPs

In the first phase, we develop a direct-relation matrix for each of fifteen managers using the linguistic scale, then set the corresponding fuzzy triangular numbers, and finally find fifteen direct-relation fuzzy matrices.

Step 1. Identifying the uncertainties and risks

Firstly, we identify the uncertainties and risks as described in the questionnaire design section. The pairwise interactions between uncertainties and risks for LSPs come from managers.

Step 2. Assessing the pairwise interactions among uncertainty and risk elements

The second step of the fuzzy DEMATEL method finds the direct-relation matrices $D^p = \left[d_{ij}^p\right]_{n\times n}$ with the data collected from p managers $(p = 1, 2, \cdots, P)$ for n uncertainties and risks $(n = 1, 2, \cdots, N)$. The diagonal elements of direct-relation matrices D^p are equal to zero since an item cannot directly influence itself according to the DEMATEL method (Tzeng et al., 2010).

$$D^p = \begin{bmatrix} 0 & d_{12}^p & \cdots & d_{1n}^p \\ d_{21}^p & 0 & \cdots & d_{2n}^p \\ \vdots & \vdots & \ddots & \vdots \\ d_{n1}^p & d_{n2}^p & \cdots & 0 \end{bmatrix}$$

Step 3. Transform the linguistic expressions into triangular fuzzy numbers

Importance weights and influence scores designated by the managers are essentially linguistic expressions. As Li (1999) suggests, for tackling the vagueness of managers' assessments, the ratings of the linguistic influence scale are converted into triangular fuzzy numbers (see Table 8). Let $F^p = \left(l_{ij}^p, m_{ij}^p, r_{ij}^p\right)$ denotes the rating of uncertainty/risk i that influences uncertainty/risk j, obtained from p managers. In the fuzzy transformation of the lingual expression, l signifies the smallest possible value, m indicates the most probable value, and r represents the largest possible value of the fuzzy phenomenon.

Table 8
The fuzzy linguistic transformation.

Linguistic scale	Influence score	Triangular fuzzy numbers
No influence	0	(0, 0, 0.25)
Very low influence	1	(0, 0.25, 0.50)
Low influence	2	(0.25, 0.50, 0.75)
High influence	3	(0.50, 0.75, 1.00)
Very high influence	4	(0.75, 1.00, 1.00)

Subsequently, we transform the direct-relation matrices D^p into the direct-relation fuzzy matrices $F^p = \left[f_{ij}^p\right]_{n\times n}$. The triangular fuzzy numbers describe the direct-relation expressions of managers for each uncertainty and risk pair. According to the fuzzy transformation, each manager response corresponds to a fuzzy number to define the direct relations between uncertainty/risk pairs. For example, with n uncertainties/risks $(n = 1, 2, \cdots, N)$ and p managers $(p = 1, 2, \cdots, P)$, the direct-relation fuzzy matrices F^p can be built as below where $f_{ij}^p = \left(l_{ij}^p, m_{ij}^p, r_{ij}^p\right)$:

$$F^p = \begin{bmatrix} 0 & f_{12}^p & \cdots & f_{1n}^p \\ f_{21}^p & 0 & \cdots & f_{2n}^p \\ \vdots & \vdots & \ddots & \vdots \\ f_{n1}^p & f_{n2}^p & \cdots & 0 \end{bmatrix}$$

3.5. Defuzzy the direct relation fuzzy matrices by the CFCS method

In the second phase, we defuzzy the direct relation fuzzy matrices by the "Converting Fuzzy data into Crisp Scores" (CFCS) defuzzification method provided by Opricovic and Tzeng (2003).

Step 4. Standardize the fuzzy numbers

According to the CFCS defuzzification method, the standardized fuzzy values are calculated as "a weighted average according to the membership functions" by using Equations (1)-(3):

$$xl_{ij}^p = \left(l_{ij}^p - \min_{1\le p\le P} l_i^p\right) \Big/ \Delta_{min}^{max} \quad (1)$$

$$xm_{ij}^p = \left(m_{ij}^p - \min_{1\le p\le P} l_i^p\right) \Big/ \Delta_{min}^{max} \quad (2)$$

$$xr_{ij}^p = \left(r_{ij}^p - \min_{1\le p\le P} l_i^p\right) \Big/ \Delta_{min}^{max} \quad (3)$$

$$\Delta_{min}^{max} = \max r_i^p - \min l_i^p$$

Step 5. Obtain the crisp numbers

Next, we defuzzy the values of the triangular fuzzy number matrices F^p to obtain the crisp values y_{ij}, and find the direct-relation defuzzy matrices $Y^p = \left[y_{ij}^p\right]_{n\times n}$. The crisp numbers are calculated according to the CFCS method by using Equation (4):

$$y_{ij}^{p} = \min l_i^{p} + x_j^{p} \Delta_{min}^{max} \tag{4}$$

Where $x_j^p = \left[xl_j^{'p}\left(1 - xl_j^{'p}\right) + xl_j^{'p} xr_j^{'p}\right] / \left(1 + xr_j^{'p} - xl_j^{'p}\right)$;

$$xl_{ij}^{'p} = xm_j^p / \left(1 + xm_j^p - xl_j^p\right)$$

$$xr_j^{'p} = xr_j^p / \left(1 + xr_j^p - xm_j^p\right)$$

Thus, we transform fuzzy numbers into crisp y_{ij}^p values.

$$Y^p = \begin{bmatrix} 0 & y_{12}^p & \cdots & y_{1n}^p \\ y_{21}^p & 0 & \cdots & y_{2n}^p \\ \vdots & \vdots & \ddots & \vdots \\ y_{n1}^p & y_{n2}^p & \cdots & 0 \end{bmatrix}$$

Step 6. Aggregate the crisp scores

In the sixth step, the average values of the direct-relation defuzzied matrices Y^p are calculated by dividing the sum of causal effect ratings by the number of respondent managers n (15) and the average direct-relation matrix $W = [w_{ij}]_{n\times n}$ is obtained (see Appendix I).

We calculate the average direct relations for all managers by using Equation (5):

$$w_{ij} = \frac{1}{P}\sum_{p=1}^{P} y_{ij}^p \tag{5}$$

Thus, we obtain the average initial direct-relation matrix $\boldsymbol{W}$.

$$W = \begin{array}{c} \begin{matrix} w_{11} & w_{12} & \cdots & w_{1n} \end{matrix} \\ \begin{bmatrix} w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \end{bmatrix} \\ \begin{matrix} w_{n1} & w_{n2} & \cdots & w_{nn} \end{matrix} \end{array}$$

3.6. *Identify cause-effect relations and key factors*

In the third phase, the cause-effect relationships among uncertainties and risks are determined, and their prominence is revealed according to the analysis results.

Step 7. Compute the normalized initial direct-relation matrix

Here, we normalize the average initial direct-relation matrix W by using Equation (6):

$$Z = W / \max_{1\le p\le P} \sum\nolimits_{j=1}^{n} w_{ij} \tag{6}$$

And obtain the normalized initial direct-relation matrix $Z = [z_{ij}]_{n\times n}$ (see Appendix II).

$$Z = \begin{array}{c} \begin{matrix} z_{11} & z_{12} & \cdots & z_{1n} \end{matrix} \\ \begin{bmatrix} z_{21} & z_{22} & \cdots & z_{2n} \\ \vdots & \vdots & \ddots & \vdots \end{bmatrix} \\ \begin{matrix} z_{n1} & z_{n2} & \cdots & z_{nn} \end{matrix} \end{array}$$

Step 8. Compute the total relation matrix

The total relation matrix $T = [t_{ij}]_{n\times n}$ is set up from the total effects that uncertainty/risk UR_i gives and receives by using Equation (7) (see Appendix III). The values in the total relation matrix T represent the sum of the row factors' direct and indirect influence on the column factors (Hinduja & Pandey, 2018). A row factor's direct influence on a column

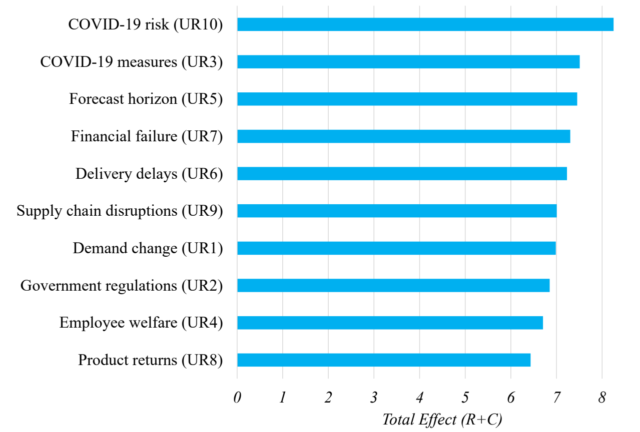

Fig. 3. The total effect graph.

factor indicates an unmediated causal effect, and indirect influence signifies a mediated causal effect through the system (Tzeng & Shen, 2017).

$$T = Z(1 - Z)^{-1} \tag{7}$$

$$T = \begin{array}{c} \begin{matrix} t_{11} & t_{12} & \cdots & t_{1n} \end{matrix} \\ \begin{bmatrix} t_{21} & t_{22} & \cdots & t_{2n} \\ \vdots & \vdots & \ddots & \vdots \end{bmatrix} \\ \begin{matrix} t_{n1} & t_{n2} & \cdots & t_{nn} \end{matrix} \end{array}$$

Step 9. Calculate the total and net effect values

In the final step, firstly, we calculate the influential (R_i) and influenced (C_i) effects and the total ($R_i + C_i$) and net effect ($R_i - C_i$) values. Then we set a threshold value θ and acquire the interdependency matrix M and the cause-effect model to construct and visualize the cause-effect relationships among uncertainties and risks.

We calculate the sum of rows (causal effects given by uncertainty/risk UR_i) and columns (causal effects received uncertainty/risk UR_i) of total relation matrix T and find the influential effect R_i and influenced effect C_i for each uncertainty and risk by using Equations (8)-(9).

$$R_i = \sum_{1\le p\le P} t_{ij} \tag{8}$$

$$C_i = \sum_{1\le p\le P} t_{ji} \tag{9}$$

The influential effect R_i values indicate the sum of direct and indirect causal effects given by uncertainty/risk UR_i to other uncertainty and risk elements in the system, the influenced effect C_i values denote the sum of direct and indirect causal effects received by uncertainty/risk UR_i from uncertainty and risk elements in the system (Tzeng & Shen, 2017). Then we calculate the total effect values ($R_i + C_i$) and the net effect values ($R_i - C_i$) for each uncertainty and risk. According to Tzeng and Shen (2017), the total effect value represents the sum of effects given and received by uncertainty/risk UR_i, while the net effect value designates the degree of net causal effect that uncertainty/risk UR_i has on the system. Uncertainty/risk UR_i has a positive net effect value $(R_i - C_i) > 0$ if its total causal effect given on the system is higher than its total causal effect received from the system. Uncertainty/risk UR_i has a negative net effect value $(R_i - C_i) < 0$ if its total causal effect received from the system is higher than its total causal effect given to the system. The total effect value is the degree of how prominent uncertainty/risk UR_i are. And the net effect value is the extent to which uncertainty/risk UR_i can affect the system and stir up other uncertainties and risks.

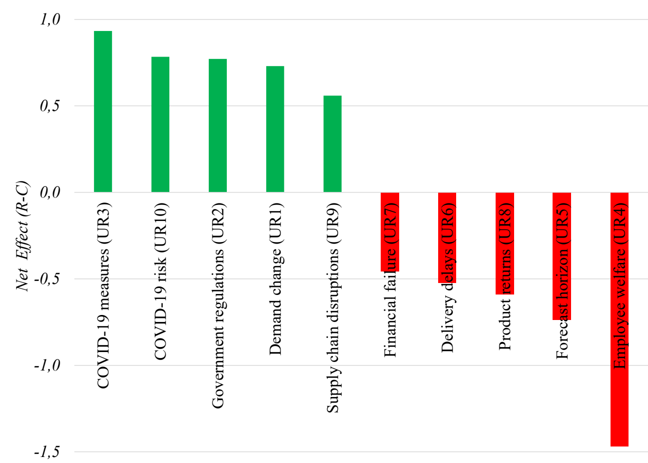

Fig. 4. The net effect diagram.

Table 9
The significance of uncertainties and risks.

Uncertainty/Risk	Significance	
	Value	Ranking
COVID-19 risk (UR_{10})	4.81	1
Employee welfare (UR_4)	4.75	2
COVID-19 measures (UR_3)	4.63	3
Forecast horizon (UR_5)	4.38	4
Supply chain disruptions (UR_9)	4.31	5
Demand change (UR_1)	4.31	6
Delivery delays (UR_6)	4.13	7
Financial failure (UR_7)	4.06	8
Government regulations (UR_2)	4.06	9
Product returns (UR_8)	3.19	10

4. Results

In this section, the analysis results of the fuzzy DEMATEL method are presented. The influential (R_i) and influenced (C_i) effects and the total $(R_i + C_i)$ and net effect $(R_i - C_i)$ values of each uncertainty and risk are shown in Appendix IV.

The prominence of uncertainties and risks are prioritized based on the total effect values. Fig. 3 presents the prominence of the uncertainties and risks arranged in the descending order of total effect value. The COVID-induced uncertainties and risks top the system. Followingly, forecast horizon, financial failure, delivery delays, supply chain disruptions, and demand change are moderately prominent. Government regulations, employee welfare, and product returns are the least prominent factors.

Fig. 4 shows the net effect value of each uncertainty and risk. As Tzeng et al. (2007) suggest, we classify the uncertainties and risks into two groups based on their net effect values. The uncertainties and risks that have a positive net effect value $(R_i - C_i) > 0$ are labeled as net causers, and the uncertainties and risks that have a negative net effect value $(R_i - C_i) < 0$ are labeled as net receivers. The COVID-induced factors have the highest net effects, which means COVID-19 measures and COVID-19 risk are the system's main drivers, i.e., net causers. Besides, government regulations, demand change, and supply chain disruptions are also grouped as net causers. Employee welfare has the lowest net effect indicating the system's main outcome, i.e., net receiver. Four other uncertainty and risk elements are identified as net receivers: forecast horizon, product returns, delivery delays, and financial failure.

The managers are asked to evaluate each uncertainty and risk's significance within the questionnaire besides assessing interrelations. The significance criteria (see Table 9) indicate the average of fifteen managers' evaluation scores on the importance of each uncertainty and risk for their operations. The managers perceive COVID-19 risk, employee welfare, and COVID-19 measures as more significant, with the highest absolute net effect values. Nonetheless, the least significant factor is product returns, followed by government regulations, financial failure, and delivery delays. The remaining factors, forecast horizon, supply chain disruptions, and demand change, have moderate significance.

Fig. 5 shows the overall prominence and causal effect diagram based on the total and net effect values and the significance criteria. The overall prominence and causal effect diagram is formed by the horizontal axis that shows the total effect $(R_i + C_i)$ and the vertical axis that shows the net effect $(R_i - C_i)$ values of uncertainties and risks. The horizontal axis shows how significant uncertainty/risk UR_i is, while the vertical axis classifies uncertainties and risks into net causer and net receiver groups. The upper part of the diagram contains net causers, while the lowermost comprises net receivers. The diameter of the circles indicates the significance criteria in Table 9. We take the fourth power of the significance criteria to make it more distinctive in the diagram.

We develop a cause-effect model (see Fig. 6) to visualize the complex causal relationships and interdependencies among uncertainties and risks using the values of the interdependency matrix M (see Appendix V) and total $(R_i + C_i)$ and net $(R_i - C_i)$ effect values. The interdependency matrix M shows the pairwise causal effect values obtained by removing elements less than the threshold value θ in the total relation matrix T.

We set a threshold value θ to filter out some negligible effects in the total relation matrix T to explain the structural relations among the uncertainty and risk factors while keeping the system's complexity manageable (Tzeng & Shen, 2017). Only uncertainty and risk factors in the total relation matrix T having an effect greater than the threshold value θ are kept in the interdependency matrix M (Tzeng et al., 2007). In the literature, the threshold value θ is usually determined by decision-maker or expert discussions (Lin & Tzeng, 2009), averaging the values of the total relation matrix T (Quezada et al., 2018), or taking the maximum value of the diagonal elements of the total relation matrix T (Tan and Kuo, 2014). If the threshold value is too low, the cause-effect model will be too complex for decision-making; in contrast, if the threshold value is too high, too many factors will be shown as independent elements without interacting with other factors (Tzeng et al., 2007). This study sets the threshold value $(\theta = 0.42)$ as the maximum to keep every element interacting with the system while reducing the complexity of the cause-effect model.

Fig. 6 shows the solution for the model in Fig. 1 suggested in the Introduction Section. The extracted solution in Fig. 6 illustrates the cause-effect model of uncertainties and risks based on the interdependency matrix in M. The solid lines represent one-way causal relationships, while dotted lines symbolize interdependencies. The lines are colored as shown in the legend to disambiguate cause-effect relationships and interdependencies among uncertainties and risks.

The results show that two uncertainties affect two risks, two risks affect three uncertainties, and one uncertainty and one risk are interdependent. Plus, three uncertainties affect two other uncertainties, and two risks affect four other risks. Specifically, COVID-19 risk, a net causer, affects all net receivers, i.e., employee welfare, forecast horizon, delivery delays, financial failure, and product returns, plus two net causer group elements, demand change, and government regulations. Two net causers, COVID-19 measures and demand change, affect all net receivers, but product returns which is only affected by COVID-19 risk. Forecast horizon, another net receiver, is affected by all five net causers, i.e., demand change, government regulations, COVID-19 measures, supply chain disruptions, and COVID-19 risk. Two other net receivers, delivery delays and financial failure, are affected by the same four net causers, all net causer group elements but government regulations. Another net receiver, employee welfare, is also affected by four net causers, but by government regulations instead of supply chain

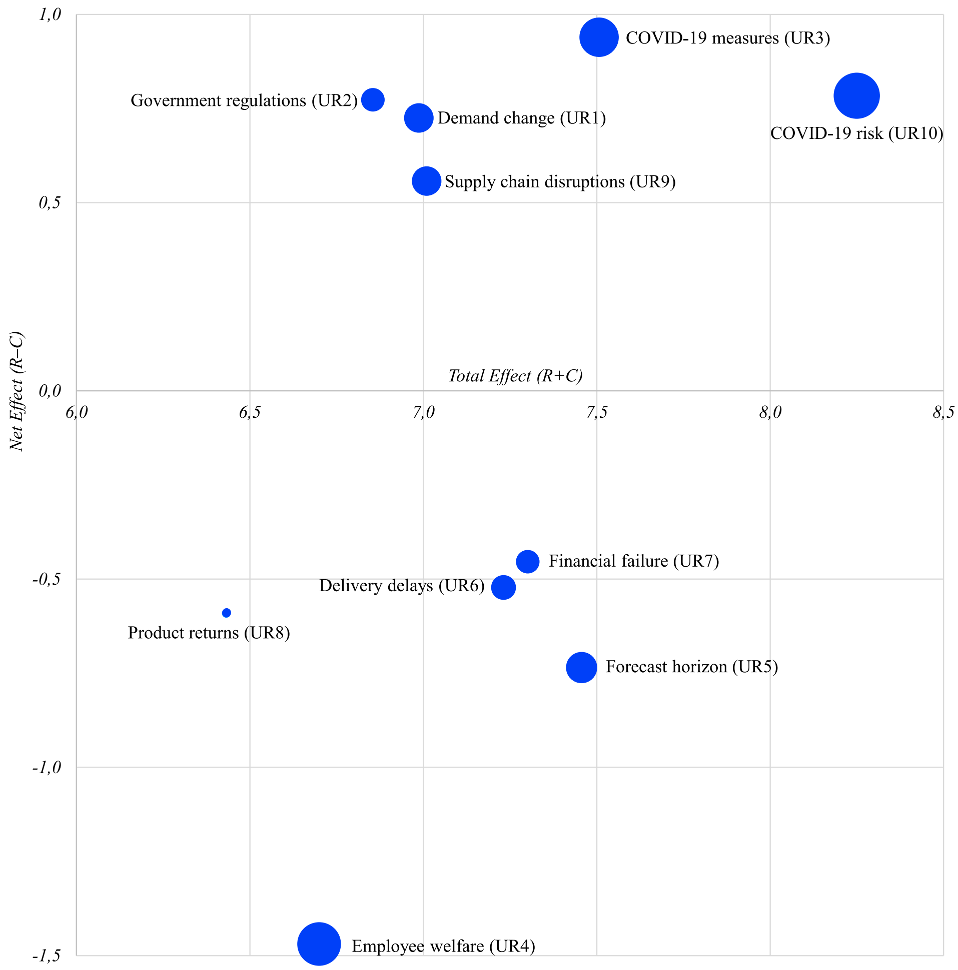

Fig. 5. The overall prominence and causal effect diagram.

disruptions. Only interrelation in the extracted model is between two net causers, COVID-19 measures and COVID-19 risk. As a result, the proposed two-way cause-effect relationship and interdependency between uncertainty and risk types are confirmed.

4.1. Sensitivity analysis of the results

Decision-makers' risk sensitivity influences their perception of risk and uncertainty magnitude (Tversky & Fox, 1995). Moreover, the actions of risk-prone or risk-averse decision-makers are extensively associated with environmental uncertainty and risk (Ben-Haim, 2000). Hence, managers' perceptions should be addressed to validate the results since risk-sensitivity influences the decision-making behavior in supply chain operations (Tsay, 2002). Figner and Weber (2011) suggest that risk-taking behavior depends on situational and idiosyncratic characteristics. Therefore, to estimate the degree of risk sensitivity in the robustness test, managers' evaluations are weighted according to job experience, management level, job responsibility, and average risk/uncertainty importance score. The robustness of the analysis results is confirmed by conducting the sensitivity analysis to test the dependability of the managers' evaluations. In line with the studies utilizing sensitivity analysis to test the DEMATEL method's robustness (Bhatia & Srivastava, 2018; Govindan et al., 2015; Seker & Zavadskas, 2017), we outline scenarios applying various combinations of different values of manager attributes. Initially, in Scenario A, equal weights are assigned to each manager. Subsequently, in Scenarios B to E, each manager's weights are altered in terms of manager attributes to analyze the causal effect relationships' variation. The weights of each manager vary in designated scenarios since they have different degrees of job experience (Scenario B), managerial level (Scenario C), job responsibility (Scenario D), and average uncertainty/risk importance score (Scenario E). The causal effect values obtained from different sensitivity analysis scenarios are presented in Fig. 7, drawing two lines for each scenario, one for the total causal effect $(R_i + C_i)$ with higher values and one for the net effect $(R_i - C_i)$ with lower values.

The sensitivity analysis suggests that the DEMATEL method's results are valid and not highly dependent on the number of participants. The structure of cause-effect relationships is consistent in different scenarios, indicating that the results reflect consulted managers' genuine opinions. To conclude, managers' responses on the causal structure of uncertainties and risks in the logistics service industry are sufficient for this study.

5. Theoretical and managerial implications

Several implications for LSP managers can be drawn from the proposed method and its relevant findings. Our study identifies the prominence and cause-effect structure of uncertainties and risks LSPs confront during the COVID-19 pandemic and guides logistics managers to determine businesses' vulnerabilities. Identifying LSPs' weaknesses and strengths is important not only in the period of COVID-19 but also in guiding them for any unexpected supply chain disruption in the future. In this way, LSPs will establish more flexible, agile, and resilient service systems by taking precautions against unexpected situations.

Our study focuses on discovering uncertainties and risks LSPs face during the COVID-19 period and analyzes their prominence and cause-

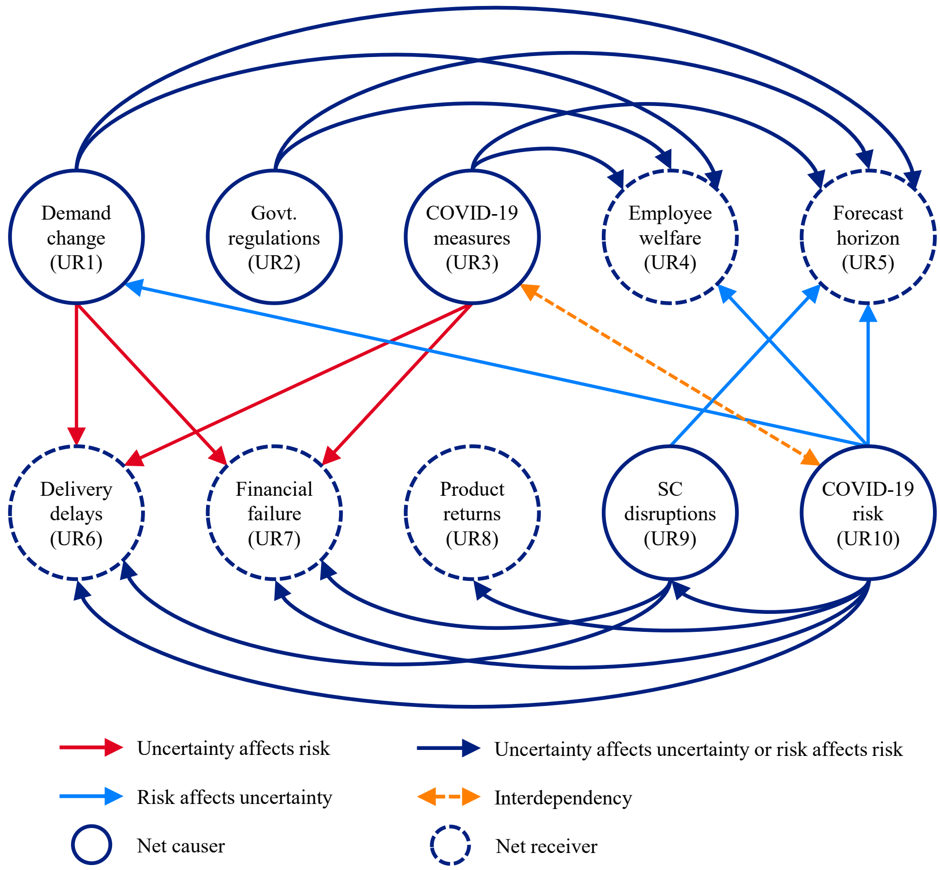

Fig. 6. The cause-effect model of uncertainties and risks.

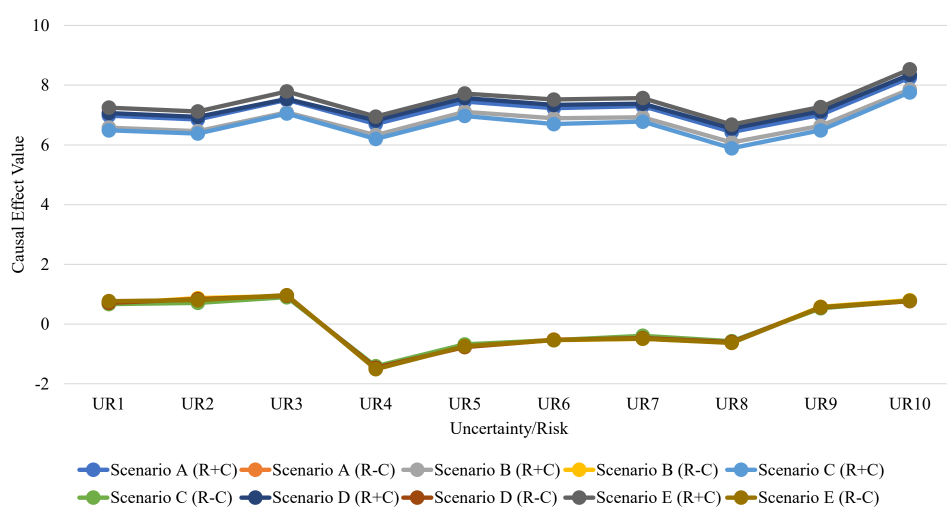

Fig. 7. Causal diagram of the sensitivity analysis.

effect structure. The proposed uncertainty and risk assessment framework offers managers and decision-makers a systematic approach to prioritize measures and decisions against COVID-19 induced risks and uncertainties. The framework augments understanding the relationship between risks and uncertainties by disclosing the cause-effect model (see Fig. 6) that illustrates the interrelations between risks and uncertainties under consideration. Hence, LSPs operating in volatile markets will be able to build flexible, agile, and resilient business models against unforeseen risks and uncertainties. The following paragraphs in this section describe the managerial implications.

Employee welfare, forecast horizon, financial failure, delivery delays, and product returns form the net receiver group. Employee welfare is the most affected factor since it has the lowest net causal effect value, implying that it is the most influenced component of the system. Employee welfare is particularly influenced by COVID-19 risk, COVID-19 measures, government regulations, and demand change, respectively. This finding is in line with the study of Dorofeev et al. (2020) that emphasizes that shipping companies' major risks are associated with human resources. Okamoto (2020) mentions the health of the employee as a recent operational risk. Although heavy truck drivers are excluded from many of the restrictions, they are unwilling to come to work due to the fear of becoming infected, and even there are cases so and more severe than that (Dorofeev et al., 2020). Besides, the supply problems in materials that need labor intensity will form a considerable share of supply chain disruptions (Chenneveau et al., 2020). However, employee welfare is an underestimated area of research. McKinsey & Company (2021) emphasizes the importance of providing a guideline when dealing with COVID-19, granting autonomy to the employees in a rapidly encountered situation, and creating a two-way communication style in terms of feeling safe. Systems to support remote working conditions and contactless logistics services (touch-free payment, mobile robots, delivery by drones) also contribute to employee welfare. A few studies (Sanchez-Rodrigues et al., 2010b; Wang et al., 2015, 2018) consider employees a part of risk and uncertainty. Sanchez-Rodrigues et al. (2010b) highlight that driver insufficiency leads to uncertainty, which is among the inefficiencies originated by the carrier. In this sense, companies consider uncertainties and risks sourcing from the employees solely in communication, shortage, and inefficiency. Wang et al. (2015) define "poor communication between company and drivers" as an internal uncertainty and risk and classify "labor/driver shortage" as an environmental uncertainty and risk. Since employee welfare relates to employee satisfaction, it is vital for companies (Bandara et al., 2020).

Forecast horizon and financial failure are among the most affected factors mainly influenced by COVID-19 measures, COVID-19 risk, government regulations, demand change, and supply chain disruptions. Volatility forecasts improve financial risk management (Christoffersen & Diebold, 2000) and help companies reduce the financial failure risk by predicting payment, cash flows, and delivery disruptions. Therefore, companies that can mitigate financial risks will be capable of making accurate forecasts. COVID-19 measures that include several arrangements (e.g., wearing masks, physical distancing, hygiene) impact the forecast horizon. COVID-19 risk has low predictability, thus complicating the long-term forecasting and unearths financial failure risks. Companies are urged to guarantee liquidity, make model simulations, and identify the factors that threaten their liquidity to prevent financial failure (McKinsey & Company, 2021). Besides, ensuring options to hedge in logistics, e.g., shipping quantity, delivery date/time, price (Tibben-Lembke & Rogers, 2006), pinpointing reliable suppliers, rebuilding a faster logistics system, and being less costly due to the advanced technology (Chenneveau et al., 2020) help companies make decisions wisely.

Product returns and delivery delays are also important factors affected by the net causer group elements. Product returns, the least prominent factor in the system, are influenced by COVID-19 risk, COVID-19 measures, demand change, and supply chain disruptions. Efficient management of reverse logistics is a vital part of the supply chains (Potdar & Rogers, 2012); managers use forecasting methods related to product returns that provide cost savings for remanufacturing (Clottey et al., 2012). Reverse logistics can be supported by authorizing third-party logistics companies to manage the maintenance, repair, and operations (MRO) function (Suyabatmaz et al., 2014). Delivery delays are influenced by COVID-19 risk, COVID-19 measures, demand change, supply chain disruptions, and government regulations. This result is associated with lockdowns, restrictions, measures, demand/supply fluctuations due to the COVID-19 pandemic (Barua, 2020).

Our findings reveal that the net causers consist of the COVID-19 measures, demand change, government regulations, COVID-19 risk, and supply chain disruptions. COVID-19 measures and COVID-19 risk are interdependent factors and have dominant causal effects on other factors for logistics companies. Choi et al. (2019) mention the influence of demand and supply uncertainties on supply chain risks. Sreedevi and Saranga (2017) emphasize the specific influence of supply uncertainty on the risks associated with the delivery lead time. McKinsey & Company (2021) reports that customer demand is the most influencing uncertainty for supply chain and production managers. We conclude that COVID-19 measures and COVID-19 risk take the first and second place in terms of the total impact on the LSPs. These are followed by government regulations, demand change, and supply chain disruptions, respectively.

Governments are policymakers or influencers that affect the external environment within which logistics operations are held. The relation between efficiency and environmental impact becomes clear for logistics managers today. For instance, government interventions such as taxation laws or regulations can stimulate many businesses to change their core strategies (Sanchez-Rodrigues et al., 2010b). Health-related government regulations such as lockdowns have an impact on supply chains. According to Mollenkopf et al. (2020), sudden shifts in health-related regulations result in serious supply chain disruptions such as farmers not being available to harvest crops, shutdowns of the food-service and restaurant sector, and productivity decline due to changing working conditions. China's social logistics costs have significantly increased during the COVID-19 period. Liu et al. (2020) state that some of the reasons for this rise are the worker shortage caused by the people's mobility restriction and struggles in planning transportation routes due to the uncertainties in traffic restrictions.

The demand change and supply chain disruptions impose difficulties on the companies making decisions on investments, manufacturing, scheduling, and forecasting. Chenneveau et al. (2020) recommend coordinating the demand planners with the sales department and the data analysts to forecast demand accurately. Crawford (2020) suggests that coordinating the continuous evaluation of the effects of COVID-19 will enable the supply chain to operate more efficiently. Similarly, Jiang et al. (2020) demonstrate that emergency coordination and command systems support logistics reliability.

To survive in an uncertain and risky environment of COVID-19, it is recommended to diversify suppliers and omnichannel distribution (McKinsey & Company, 2021), hold more inventory, invest in automation (Okamoto, 2020), and reorganize the inventory management system (Crawford, 2020). As company executives may face pandemic-like disruptions in the future, they should develop some digital strategies to overcome problems such as market uncertainty and supply chain challenges. These strategies include adapting to technologies such as the Internet of Things, artificial intelligence, robotics, and 5G, as the digital transformation of supply networks is geared to anticipate and solve future challenges with advanced features (Kilpatrick & Barter, 2020). Moreover, adopting Industry 4.0 technologies such as horizontal and vertical integration, augmented reality, cloud computing, blockchain technology will help companies reduce COVID-related uncertainties and risks by decreasing human intervention.

In-depth interviews conducted in this study reveal that major problems posed by uncertainties and risks for LSP companies during the COVID-19 pandemic are: decrease in cash flow, lack of continuity in production and distribution operations, thus increasing the risks, suspension of mergers and acquisitions in the industry, and demand fluctuations in sub-sectors disrupting the supply chain. Also, findings disclose that cause-effect structure of uncertainties and risks can contribute to LSPs' by helping them to develop and review the employee welfare strategy to avoid workflow disruption, reestablish distribution planning against demand and supply disruptions, reanalyze customers' and suppliers' financial situations, find new alternatives in the supply chain network, reevaluate contracts and insurance coverages for force majeure, digitize communication and business processes, and ensure flexibility in working conditions and durations.

6. Conclusions and discussion

Supply chains and LSPs operating in today's complex environment (Nilsson, 2006) are vulnerable to the associated uncertainties and risks. According to several studies (Christopher & Lee, 2004; Sanchez-Rodrigues et al., 2010b; Sreedevi & Saranga, 2017), uncertainty causes supply chain risk. Contrarily, Calatayud et al. (2017) assert that risks boost uncertainty in a complex environment such as logistics. We merge

Table A1
The average initial direct-relation matrix.W

	UR_1	UR_2	UR_3	UR_4	UR_5	UR_6	UR_7	UR_8	UR_9	UR_{10}
UR_1	0.00	0.47	0.44	0.69	0.87	0.83	0.81	0.61	0.83	0.55
UR_2	0.69	0.00	0.76	0.73	0.66	0.66	0.70	0.42	0.52	0.75
UR_3	0.81	0.78	0.00	0.86	0.69	0.69	0.75	0.47	0.66	0.89
UR_4	0.14	0.44	0.50	0.00	0.38	0.52	0.38	0.36	0.45	0.73
UR_5	0.42	0.47	0.44	0.75	0.00	0.66	0.61	0.81	0.42	0.69
UR_6	0.31	0.34	0.52	0.78	0.75	0.00	0.62	0.81	0.41	0.72
UR_7	0.44	0.44	0.70	0.72	0.78	0.52	0.00	0.72	0.36	0.66
UR_8	0.41	0.33	0.34	0.42	0.69	0.66	0.75	0.00	0.55	0.38
UR_9	0.80	0.53	0.48	0.58	0.83	0.89	0.76	0.67	0.00	0.42
UR_{10}	0.89	0.87	0.87	0.86	0.83	0.70	0.73	0.52	0.83	0.00

these two opposite claims by concluding that uncertainties and risks are intertwined.

The major contribution of our study is threefold. First, we identify the uncertainties and risks that LSPs encounter during the COVID-19 pandemic and demonstrate prominent ones. Second, we unveil the intertwined cause-effect structure of uncertainties and risks. Third, we provide an uncertainty and risk assessment guideline for LSPs operating in uncertain business environments shaped by the threats that emerged from unprecedented crises such as the COVID-19 pandemic.

Our study proposes a decision-making framework for LSPs by incorporating uncertainty and risk factors that affect their vulnerability in case of adverse events such as outbreaks, natural disasters, economic crises, regional conflicts, and force majeure. Our study combines the qualitative and MCDM methods to identify uncertainties and risks that LSPs encounter during the COVID-19 pandemic and investigate their prominence and cause-effect structure. At first, we conduct in-depth interviews and identify the uncertainties and risks via qualitative thematic analysis. Then, we collect data from LSP managers regarding the crippling effects of the novel coronavirus pandemic on the logistics industry and analyze their opinions on pairwise relations among uncertainties and risks by conducting the fuzzy DEMATEL method. We expose uncertainties and risks' prominence and interrelations and cluster them into net causer and net receiver groups. Afterward, we illustrate the cause-effect structure of the uncertainties and risks and provide an uncertainty and risk assessment tool for LSP companies.

Our framework assists managers and decision-makers in allocating resources that require greater attention to companies in response to contingencies such as the COVID-19 pandemic. The proposed methodological framework in our study provides insights to the managers and decision-makers on how to prioritize uncertainties and risks to mitigate the negative impacts of adverse events such as the COVID-19 pandemic. The implications provided to the managers by applying the proposed framework guide them through the strategic decisions on allocating resources to counter unforeseeable threats. Companies prepare for unexpected situations and create a more flexible, agile, and resilient logistics service infrastructure by creating more effective resource planning. These capabilities improve customer service and satisfaction and give LSPs a competitive edge to outperform their competitors.

7. Limitations and directions for future research

The COVID-19 pandemic affects the LSPs unequally, although the pandemic's real impact on the global supply chains is unknown (Twinn et al., 2020). Accordingly, some LSPs serving the e-commerce market positively experience the COVID-19 shock by increased volume in their operations, while others negatively experience the crisis by delivery delays, congestions, and higher transportation rates (Pitel, 2020). In future studies, sector-specific samples (e.g., food, medical, automotive, appliances, textile) can be studied.

Our study is conducted with data collected from the managers of the LSPs operating in Turkey. Further research is needed to illustrate employees' perspectives and compare managers and employees. More than half of our sample consists of large-scale companies operating in different businesses, e.g., diversified segments, sectors, and markets, which are more resilient to threats (Twinn et al., 2020). Likewise, large-scale LSPs manage risks associated with environmental and social sustainability issues better than the smaller ones (Multaharju et al., 2017). Overseas logistics experience more problems during the COVID-19 pandemic due to longer lead times and higher delivery costs (Chenneveau et al., 2020). Therefore, further research can reflect the effects of company size or logistics mode. Our study focuses on how LSP managers evaluate uncertainties and risks, and future studies are needed to investigate how LSPs control and mitigate risks during adverse events.

CRediT authorship contribution statement

Beyza Gultekin: Resources, Writing – original draft, Writing – review & editing. **Sercan Demir:** Conceptualization, Methodology, Validation, Formal analysis, Writing – original draft. **Mehmet Akif Gunduz:** Conceptualization, Methodology, Validation, Formal analysis, Writing –

Table A2
The normalized initial direct-relation matrix.Z

	UR_1	UR_2	UR_3	UR_4	UR_5	UR_6	UR_7	UR_8	UR_9	UR_{10}
UR_1	0.00	0.07	0.06	0.10	0.12	0.12	0.11	0.09	0.12	0.08
UR_2	0.10	0.00	0.11	0.10	0.09	0.09	0.10	0.06	0.07	0.11
UR_3	0.11	0.11	0.00	0.12	0.10	0.10	0.11	0.07	0.09	0.13
UR_4	0.02	0.06	0.07	0.00	0.05	0.07	0.05	0.05	0.06	0.10
UR_5	0.06	0.07	0.06	0.11	0.00	0.09	0.09	0.11	0.06	0.10
UR_6	0.04	0.05	0.07	0.11	0.11	0.00	0.09	0.11	0.06	0.10
UR_7	0.06	0.06	0.10	0.10	0.11	0.07	0.00	0.10	0.05	0.09
UR_8	0.06	0.05	0.05	0.06	0.10	0.09	0.11	0.00	0.08	0.05
UR_9	0.11	0.07	0.07	0.08	0.12	0.13	0.11	0.09	0.00	0.06
UR_{10}	0.13	0.12	0.12	0.12	0.12	0.10	0.10	0.07	0.12	0.00

Table A3
The total relation matrix.T

	UR_1	UR_2	UR_3	UR_4	UR_5	UR_6	UR_7	UR_8	UR_9	UR_{10}
UR_1	0.27	0.32	0.34	0.44	0.46	0.44	0.44	0.38	0.38	0.39
UR_2	0.35	0.26	0.38	0.44	0.43	0.41	0.42	0.35	0.34	0.41
UR_3	0.40	0.39	0.31	0.49	0.47	0.45	0.46	0.39	0.39	0.46
UR_4	0.21	0.24	0.26	0.24	0.29	0.29	0.28	0.25	0.25	0.31
UR_5	0.29	0.29	0.30	0.40	0.31	0.37	0.37	0.37	0.30	0.37
UR_6	0.27	0.27	0.31	0.40	0.40	0.29	0.37	0.37	0.29	0.37
UR_7	0.30	0.29	0.34	0.40	0.41	0.36	0.29	0.36	0.29	0.37
UR_8	0.26	0.24	0.26	0.32	0.36	0.34	0.35	0.23	0.28	0.29
UR_9	0.36	0.32	0.34	0.42	0.45	0.44	0.42	0.39	0.27	0.37
UR_{10}	0.43	0.42	0.44	0.52	0.52	0.48	0.48	0.42	0.43	0.38

Table A4
Total and net effect values.

	UR_1	UR_2	UR_3	UR_4	UR_5	UR_6	UR_7	UR_8	UR_9	UR_{10}
R_i	3.86	3.81	4.22	2.62	3.36	3.35	3.42	2.92	3.78	4.52
C_i	3.13	3.04	3.29	4.09	4.10	3.88	3.88	3.51	3.22	3.73
$R_i + C_i$	6.98	6.85	7.51	6.70	7.45	7.23	7.30	6.43	7.01	8.25
$R_i - C_i$	0.73	0.77	0.93	−1.47	−0.74	−0.52	−0.46	−0.59	0.56	0.78

Table A5
The interdependency matrix.M

	UR_1	UR_2	UR_3	UR_4	UR_5	UR_6	UR_7	UR_8	UR_9	UR_{10}
UR_1				0.44	0.46	0.44	0.44			
UR_2				0.44	0.43					
UR_3				0.49	0.47	0.45	0.46			0.46
UR_4										
UR_5										
UR_6										
UR_7										
UR_8										
UR_9					0.45	0.44	0.42			
UR_{10}	0.43		0.44	0.52	0.52	0.48	0.48	0.42	0.43	

original draft. **Fatih Cura:** Resources, Writing – original draft, Data curation. **Leyla Ozer:** Resources, Writing – review & editing, Supervision.

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.

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Appendix

(See Tables A1-A5)

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