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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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ABSTRACT

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
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.

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### 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 Chaudhari (2016) | X | DEMATEL | Logistics service industry |
| Modledi 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-Sona et al. (2018) | X | Structural equation modeling | Logistics service industry |
| This study     | 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,
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 (Galatayud 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 (Shahbazi 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
supply and demand risks (e.g., mismatching supply and demand with supply chain. A strong interdependence exists between uncertainty and insufficient buffer stock) (Stewart, 2021) may cause uncertainty in the supply chain risks (e.g., inadequate departmental coordination) and internal problems in unloading and loading, an internal risk, results in

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 possibilities 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 & Bak, 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.

### Table 3

| Reference | Supply risk | Demand risk | Internal risk | External risk |
|-----------|-------------|-------------|---------------|---------------|
| Funniyamooity et al. (2013) | Poor quality of supplies | Unanticipated or volatile customer | Information risks | Policy uncertainty |
|                      | Short supplies | Significant forecast error in demand | Wrong choice of transportation mode | Macroeconomic uncertainty |
|                      | Delays in supply lead-time | Receivable risks | Damages due to accidents or improper stock | Uncertainty due to government laws and regulations |
|                      | Bankruptcy of suppliers | Change in customer preference | Unavailability of special vehicles | Social uncertainty |
|                      | Disruption in production | Reputation risk | Frequent delays in delivery | Nonavailability of skilled workforce |
|                      | Low production capability | | | Force majeure |
|                      | Inflexibility in capacity | | | |
| Govindan and Chaudhuri (2016) | Bankruptcy of suppliers | Seasonality | Failure of IT systems | Buyer and supplier relationship risks |
| Konig and Spiner (2016) | Low production yield | New product adaptions | Delayed deliveries | Terrorist attracts |
|                      | Wrong order quantities | The volatile customer | | Labor strikes |
| Modemi et al. (2016) | | | | Socio-political crises |
| Baharmand et al. (2017) | | | | Force majeure |
| | | | | Industry risk |
| Calatayud et al. (2017) | | | | Market fluctuations |
| Multaharju et al. (2017) | | | | Natural disasters |
| Prakash et al. (2017) | Outsourcing that causes supply problems | Fluctuations in demand | Inaccurate forecasting | Economic downturns |
| | Control risk in supply chain variables | | | Terrorism |
| | Process risks related to value-added activities | | | |
| Streevi and Saranga (2017) | Process risks | | | Delivery risks |
| Gouda and Saranga (2018) | Actual supply chain risks | | | |
| Jaja et al. (2018) | Supply risks | | | |
| | Process risks | | | |
| Tari et al. (2018) | Crude supply | Fluctuations in demand | Failure of IT systems | Natural disasters |
| | Property damage | Inaccurate forecasting | Merger/alliance | Man-made disasters |
| | Low capacity | Poor prediction of customer demand | Intellectual property trust | Legal/political risks |
| | | | Leadership and management style | Economic crisis |
| | | | Delayed deliveries | Transportation accidents |
| | | | | Vandalism during transportation |
| | | | | Threats from competitors |
| Ramesh et al. (2019) | Supplier performance risks | | | Natural disasters |
| | Suppliers’ supply management | | | Man-made disasters |
| | Product-related risks | | | Legal/political risks |
| | Previous supplier score | | | Economic crisis |
| | Product-related risk | | | |
| Shahbaz et al. (2019) | Supply risks | Demand risks | Collaboration risks | Environmental risks |
| | Process risks | Financial risks | Logistics risks | |
| Wang et al. (2020) | Manufacturing risks | Customer risks | Financial failure | Environmental risks |
| This study | Supply chain disruptions | Product returns | COVID-19 risk | Delivery delays |
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) defuzzifying 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 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 4**

| 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 |
Having this up-to-date knowledge and experience would allow experts to contribute practical knowledge in the logistics services industry. Second, they should have broad experience and knowledge in the logistics services industry. According to Verkooij and Spruit (2013), the expert selection protocol is based upon two criteria. First, experts should have broad experience and knowledge in the logistics services industry. Second, they should have broad experience and knowledge in the logistics services industry. 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 category. 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. (2010) 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 as an environmental uncertainty and risk. Decrease of human mobility

| 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 | RF1 |
| IT & control/tracking systems failure | Risk | Internal | 2 | RF2 |
| Road accidents | Risk | Internal | 3 | RF3 |
| Logistics safety (e.g., safe movement of people and goods) | Risk | Internal | 4 | RF4 |
| Delivery delays | Risk | Internal | 5 | RF5 |
| Improper handling, packaging, loading, and shipping | Risk | Internal | 6 | RF6 |
| Damage and loss | Risk | Internal | 7 | RF7 |
| Cyber-security infrastructure unavailability | Risk | Internal | 8 | RF8 |
| 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 category. 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.

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| 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 |
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| Supply chain disruptions | Risk | Supply | 5 | RS5 |
| Product recalls | Risk | Supply | 6 | RS6 |
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| Delivery delays | Risk | Internal | 5 | RF5 |
| Improper handling, packaging, loading, and shipping | Risk | Internal | 6 | RF6 |
| Damage and loss | Risk | Internal | 7 | RF7 |
| Cyber-security infrastructure unavailability | Risk | Internal | 8 | RF8 |
| 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 |
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.

| Denotation | Item Description | Reference |
|------------|------------------|-----------|
| UR<sub>1</sub> | Demand change | Variation in quantity, timing, specifications, delivery, and preferences | Avellar-Sosa et al. (2018), Kazemi, Zanjani, and Nourrellah (2014) |
| UR<sub>2</sub> | Government regulations | Imposition of prohibitions and restrictions by state administrations | Mutiahaia et al. (2017), Simangunsong et al. (2012) |
| UR<sub>3</sub> | COVID-19 measures | Preventative actions taken in response to the COVID-19 | P. Sharma et al. (2020) |
| UR<sub>4</sub> | Employee welfare | Quality of health, well-being, and happiness of the employees | Kekkonen et al. (2018) |
| UR<sub>5</sub> | Forecast horizon | The period for which LSPs can predict the future | Liu et al. (2015), Simangunsong et al. (2012) |
| UR<sub>6</sub> | Delivery delays | Delay in order processing, shipping, or delivery | Baharmand et al. (2017) |
| UR<sub>7</sub> | Financial failure | Disruptions in the payments and remittance or sudden default or bankruptcy | Hwang and Kim (2018), R. Sharma et al. (2020) |
| UR<sub>8</sub> | Product returns | Rejections or returns of goods | Martino et al. (2015), Robertson et al. (2020), Yahlabik et al. (2005) |
| UR<sub>9</sub> | Supply chain disruptions | Disruptions in the production and the flow of goods | Choi (2021), Choi et al. (2016) |
| UR<sub>10</sub> | COVID-19 risk | Health complications associated with the COVID-19 | R. Sharma et al. (2020) |

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 expertise and experience 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).

| 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                | 133                 | 1000 or more                      | Courier shipment, transportation, warehousing |
| M3  | Warehouse manager | 21                | 23                  | 250 to 499                        | Courier shipment        |
| M4  | CEO            | 14                | 33                  | 500 to 999                        | Couriership              |
| 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 management systems, warehousing |
| M9  | Board chairman | 13                | 13                  | 1 to 50                           | Transportation, transportation management systems, warehousing |
| M10 | Direct sales manager | 19              | 57                  | 500 to 999                        | Transportation, transportation management systems, warehousing |
| M11 | Team leader    | 16                | 32                  | 500 to 999                        | Plant logistics, 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, transportation management systems, warehousing |
| 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 |

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                | 133                 | 1000 or more                      | Courier shipment, transportation, warehousing |
| M3  | Warehouse manager | 21                | 23                  | 250 to 499                        | Courier shipment        |
| M4  | CEO            | 14                | 33                  | 500 to 999                        | Couriership              |
| 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 management systems, warehousing |
| M9  | Board chairman | 13                | 13                  | 1 to 50                           | Transportation, transportation management systems, warehousing |
| M10 | Direct sales manager | 19              | 57                  | 500 to 999                        | Transportation, transportation management systems, warehousing |
| M11 | Team leader    | 16                | 32                  | 500 to 999                        | Plant logistics, 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, transportation management systems, warehousing |
| 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 $D^p = \left[ d_{ij}^p \right]_{i=1\ldots n, j=1\ldots n}^p$ with the data collected from $p$ managers ($p = 1, 2, \ldots, P$) for $n$ uncertainties and risks ($n = 1, 2, \ldots, N$). 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).

\[
D^p = \begin{bmatrix}
0 & d_{12}^p & \cdots & d_{1n}^p \\
\vdots & \ddots & \ddots & \vdots \\
d_{i1}^p & \cdots & 0 & d_{in}^p \\
d_{12}^p & \cdots & \cdots & 0
\end{bmatrix}
\]

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 $F^p = \left( f_{ij}^p, m_{ij}^p, r_{ij}^p \right)$ denotes the rating of uncertainty/risk $i$ that influences uncertainty/risk $j$, obtained from $p$ managers. In the fuzzy transformation of the linguistic expression, $l$ signifies the smallest possible value, $m$ indicates the most probable value, and $r$ represents the largest possible value of the fuzzy phenomenon.

Subsequently, we transform the direct-relation matrices $D^p$ into the direct-relation fuzzy matrices $F^p = \left[ f_{ij}^p \right]_{i=1\ldots n, j=1\ldots n}^p$. 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 ($n = 1, 2, \ldots, N$) and $p$ managers ($p = 1, 2, \ldots, P$), the direct-relation fuzzy matrices $F^p$ can be built as below where $f_{ij}^p = \left( f_{ij}^p, m_{ij}^p, r_{ij}^p \right)$:

\[
F^p = \begin{bmatrix}
0 & f_{12}^p & \cdots & f_{1n}^p \\
\vdots & \ddots & \ddots & \vdots \\
f_{i1}^p & \cdots & 0 & f_{in}^p \\
f_{12}^p & \cdots & \cdots & 0
\end{bmatrix}
\]

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):

\[
x_l^p = \left( l - \min_{1\leq p\leq P} l^p \right) / \Delta_{l_{\text{max}}-l_{\text{min}}}
\]  

(1)

\[
x_m^p = \left( m - \min_{1\leq p\leq P} m^p \right) / \Delta_{m_{\text{max}}-m_{\text{min}}}
\]  

(2)

\[
x_r^p = \left( r - \min_{1\leq p\leq P} r^p \right) / \Delta_{r_{\text{max}}-r_{\text{min}}}
\]  

(3)

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 $F^p = \left[ y_{ij}^p \right]_{i=1\ldots n, j=1\ldots n}$. The crisp numbers are calculated according to the CFCS method by using Equation (4):

\[
y_{ij}^p = \left( y_{ij}^p, m_{ij}^p, r_{ij}^p \right)
\]
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\[ y^*_y = \min_{z} + \chi^*_y \Delta_{\min}^{\text{out}} \]

Where \( x^*_y = [\chi^*_y (1 - \chi^*_y) + \chi^*_y \chi^*_y] / (1 + \chi^*_y - \chi^*_y) \);

\[ x^*_y = \chi^*_y / (1 + \chi^*_y - \chi^*_y) \]

\[ x^*_y = \chi^*_y / (1 + \chi^*_y - \chi^*_y) \]

Thus, we transform fuzzy numbers into crisp values.

\[
\begin{bmatrix}
0 & y^*_y & \cdots & y^*_y \\
y^*_y & 0 & \cdots & y^*_y \\
\vdots & \vdots & \ddots & \vdots \\
y^*_y & y^*_y & \cdots & 0
\end{bmatrix}
\]

\[ \text{Step 6. Aggregate the crisp scores} \]

In the sixth step, the average values of the direct-relation defuzzied matrices \( W^* \) are calculated by dividing the sum of causal effect ratings by the number of respondent managers \( n \) (15) and the average direct-relation matrix \( W = [w^*_{ij}]_{i,n} \) is obtained (see Appendix I). We calculate the average direct relations for all managers by using Equation (5):

\[ w^*_{ij} = \frac{1}{p} \sum_{i=1}^{p} y^*_{ij} \] (5)

Thus, we obtain the average initial direct-relation matrix \( W \).

\[
W = \begin{bmatrix}
w_{11} & w_{12} & \cdots & w_{1n} \\
w_{21} & w_{22} & \cdots & w_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
w_{n1} & w_{n2} & \cdots & w_{nn}
\end{bmatrix}
\]

\[ \text{Step 7. Compute the normalized initial direct-relation matrix} \]

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

\[ Z = W / \max_{1 \leq i < j \leq n} \sum_{i=1}^{n} w^*_{ij} \] (6)

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

\[
\begin{bmatrix}
z_{11} & z_{12} & \cdots & z_{1n} \\
z_{21} & z_{22} & \cdots & z_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
z_{n1} & z_{n2} & \cdots & z_{nn}
\end{bmatrix}
\]

\[ \text{Step 8. Compute the total relation matrix} \]

The total relation matrix \( T = [t_{ij}]_{i,n} \) is set up from the total effects that uncertainty/risk \( UR \) 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 factor indicates an unmediated causal effect, and indirect influence signifies a mediated causal effect through the system (Tzeng & Shen, 2017).

\[ T = Z(1 - Z)^{-1} \] (7)

\[
T = \begin{bmatrix}
t_{11} & t_{12} & \cdots & t_{1n} \\
t_{21} & t_{22} & \cdots & t_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
t_{n1} & t_{n2} & \cdots & t_{nn}
\end{bmatrix}
\]

\[ \text{Step 9. Calculate the total and net effect values} \]

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 \( \theta \) 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 \( UR \)) and columns (causal effects received uncertainty/risk \( UR \)) 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).

\[ R_i = \sum_{j=1}^{p} t_{ij} \] (8)

\[ C_i = \sum_{j=1}^{p} t_{ji} \] (9)

The influential effect \( R_i \) values indicate the sum of direct and indirect causal effects given by uncertainty/risk \( UR \) 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 \( UR \) 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 \( UR \), while the net effect value designates the degree of net causal effect that uncertainty/risk \( UR \) has on the system. Uncertainty/risk \( UR \) 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 \( UR \) 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 \( UR \) are. And the net effect value is the extent to which uncertainty/risk \( UR \) can affect the system and stir up other uncertainties and risks.
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. 4 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 causing factors, 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 ($θ = 0.42$) 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 receivers, 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 causes, 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 causes, all net cause group elements but government regulations. Another net receiver, employee welfare, is also affected by four net causes, but by government regulations instead of supply chain.
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 (Tsai, 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 \( \left( R_i + C_i \right) \) with higher values and one for the net effect \( \left( R_i - C_i \right) \) 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-effect relationships. The results indicate that the DEMATEL method is a suitable approach for identifying and prioritizing the most significant uncertainty and risk factors. Furthermore, the sensitivity analysis confirms the robustness of the results and highlights the importance of considering decision-makers’ perceptions in the decision-making process. The theoretical and managerial implications drawn from this study provide valuable insights for LSP managers to better understand and manage uncertainties and risks during the COVID-19 pandemic and beyond.
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. (2016b) 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 uneartns 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
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 Demiri: Conceptualization, Methodology, Validation, Formal analysis, Writing – original draft. Mehmet Akif Gunduz: Conceptualization, Methodology, Validation, Formal analysis, Writing –

Table A1
The average initial direct-relation matrix $W$

| UR1 | UR2 | UR3 | UR4 | UR5 | UR6 | UR7 | UR8 | UR9 | UR10 |
|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|
| 0.00 | 0.47 | 0.44 | 0.69 | 0.87 | 0.83 | 0.81 | 0.61 | 0.83 | 0.55 |
| 0.69 | 0.00 | 0.76 | 0.73 | 0.66 | 0.66 | 0.00 | 0.52 | 0.00 | 0.75 |
| 0.81 | 0.78 | 0.00 | 0.86 | 0.69 | 0.69 | 0.75 | 0.47 | 0.66 | 0.89 |
| 0.14 | 0.44 | 0.50 | 0.00 | 0.38 | 0.52 | 0.38 | 0.36 | 0.45 | 0.73 |
| 0.42 | 0.47 | 0.44 | 0.75 | 0.00 | 0.66 | 0.61 | 0.81 | 0.42 | 0.69 |
| 0.31 | 0.34 | 0.52 | 0.78 | 0.75 | 0.00 | 0.62 | 0.81 | 0.41 | 0.72 |
| 0.44 | 0.44 | 0.70 | 0.72 | 0.78 | 0.52 | 0.00 | 0.72 | 0.36 | 0.66 |
| 0.41 | 0.33 | 0.34 | 0.42 | 0.69 | 0.66 | 0.75 | 0.00 | 0.55 | 0.38 |
| 0.80 | 0.53 | 0.48 | 0.58 | 0.83 | 0.89 | 0.76 | 0.67 | 0.00 | 0.42 |
| 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.

Table A2
The normalized initial direct-relation matrix $Z$

| UR1 | UR2 | UR3 | UR4 | UR5 | UR6 | UR7 | UR8 | UR9 | UR10 |
|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|
| 0.00 | 0.07 | 0.06 | 0.10 | 0.12 | 0.12 | 0.11 | 0.09 | 0.12 | 0.08 |
| 0.10 | 0.00 | 0.11 | 0.10 | 0.09 | 0.09 | 0.10 | 0.06 | 0.07 | 0.11 |
| 0.11 | 0.11 | 0.00 | 0.12 | 0.10 | 0.10 | 0.11 | 0.07 | 0.09 | 0.13 |
| 0.02 | 0.06 | 0.07 | 0.00 | 0.05 | 0.07 | 0.05 | 0.05 | 0.06 | 0.10 |
| 0.06 | 0.07 | 0.06 | 0.11 | 0.00 | 0.09 | 0.09 | 0.11 | 0.06 | 0.10 |
| 0.04 | 0.05 | 0.07 | 0.11 | 0.11 | 0.00 | 0.09 | 0.11 | 0.06 | 0.10 |
| 0.06 | 0.06 | 0.10 | 0.10 | 0.11 | 0.07 | 0.00 | 0.10 | 0.05 | 0.09 |
| 0.06 | 0.05 | 0.05 | 0.06 | 0.10 | 0.09 | 0.11 | 0.00 | 0.08 | 0.05 |
| 0.11 | 0.07 | 0.07 | 0.08 | 0.12 | 0.13 | 0.11 | 0.09 | 0.00 | 0.06 |
| 0.13 | 0.12 | 0.12 | 0.12 | 0.12 | 0.10 | 0.10 | 0.07 | 0.12 | 0.00 |
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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None.

Appendix

(See Tables A1-A5)

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