THE REPUBLIC OF TURKEY

İSTANBUL KÜLTÜR UNIVERSITY

INSTITUTE OF GRADUATE STUDIES

THE IMPACT OF SUPPLY CHAIN RISK MANAGEMENT PRACTICES ON PERFORMANCE DURING COVID-19 PANDEMIC

MASTER OF SCIENCE THESIS

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Department: Industrial Engineering

Program: Engineering Management

Supervisor: Assist. Prof. Zeynep GERGİN

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M.Sc. Thesis

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04/01/2023 Lama ABDEL-RAHMAN

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LIST OF SYMBOLS

A	Assessment
API	Active Pharmaceutical Ingredient
AVE	Average Variance Extracted
C	Control
CCA	Confirmatory Composite Analysis
COVID-19	Coronavirus Disease 2019
CR	Composite Reliability
CS	Customer Satisfaction
DC	Distribution Center
DI	Disruption Impact
DM	Decision Makers
e	Margin Error
$\mathbf{f^2}$	Effect Size
H	Hypothesis
HILP	High-Impact, Low-Probability
HTMT	Heterotrait-Monotrait Ratio of Correlations
I	Identification
IPMA	Importance Performance Map Analysis
ISM	Institute for Supply Management
JIT	Just-In-Time
K	PLSpredict Number of Subgroups
L	Likelihood
LM	Linear Model
M	Mean
M	Mitigation
MAE	Mean Absolute Error
n	Sample Size
N	Population Size
O	Outcomes
p	Population Proportion

PICK	Possible, Implement, Challenge and Kill
PLS	Partial Least Squares
PSCP	Pharmaceutical Supply Chain Performance
Q2	Stone-Geisser's Value
Q2predict	Stone-Geisser's Value of PLSpredict Algorithm
QC	Quality Control
R	Range
R&D	Research and Development
R^2	Determination Coefficient
RA	Risk Assessment
RC	Risk Control
RE	Resilience
RI	Risk Identification
RM	Risk Management
RMSE	Root Mean Square Error
RO	Robustness
SC	Supply Chain
SCM	Supply Chain Management
SCP	Supply Chain Performance
SCR	Supply Chain Risk
SCRES	Supply Chain Resilience
SCRM	Supply Chain Risk Management
SCROS	Supply Chain Robustness
SEM	Structural Equation Modeling
SGK	Sosyal Güvenlik Kurumu
TOL	Tolerance
TUIK	Türkiye İstatistik Kurumu
VB-SEM	Variance Based Structural Equational Modeling
VIF	Variance Inflation Factor
WHO	World Health Organization
Z	Z-Score
β	Beta Coefficient
σ	Variance

Üniversite : **İstanbul Kültür Üniversitesi**
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Tez Danışmanı : **Dr. Öğretim Üyesi Zeynep GERGİN**
Tez Türü ve Tarihi : **Yüksek Lisans – Ocak 2023**

ÖZET

COVID-19 PANDEMİSİ DÖNEMİNDE TEDARİK ZİNCİRİ RİSK YÖNETİMİ UYGULAMALARININ PERFORMANSA ETKİSİ

Lama ABDEL-RAHMAN

Bu çalışma, COVID-19 salgını bağlamında, tedarik zinciri risk yönetiminin tedarik zincirinin dayanıklılığı ve sağlamlığı üzerindeki etkilerini azaltmada rolünü araştırmaktadır. Bu alanda az sayıda çalışma yapılmış olsa da, ülke ve sektöre göre değişen etkileri olduğu görülmektedir. Bu motivasyonla, 102 Türk ilaç firmasından veri toplanmış ve kısmi en küçük kareler yapısal eşitlik modellemesine (PLS-SEM) dayalı doğrulayıcı bileşik analiz (CCA) kullanılarak analiz edilmiştir. Hipotez testi sonuçları, COVID-19'un tedarik zinciri risk yönetimi uygulamaları, tedarik zicirinin dayanıklılığı ve sağlamlığı üzerindeki olumsuz etkisini göstermektedir. Bu sonuç, salgının tedarik zinciri risk yönetimi uygulamaları üzerindeki olumsuz etkisini ve yıkıcı etkiyi absorbe ettikten sonra tedarik zincirinin performansını geri kazanma yeteneklerini göstermektedir. COVID-19'un, çok az firmanın önceden tahmin edebildiği ani küresel etkilerin büyüklüğü nedeniyle, firmaların tedarik zinciri risklerini nasıl tanımladığı ve kontrol ettiği üzerinde olumsuz bir etkisi olduğu görülmüştür. Bulgular, COVID-19 etkilerinin esas olarak tedarik zinciri dayanıklılığını etkilediğini göstermektedir. Ancak, şirketlerin çoğu krizden sonra planlanan performanslarını sürdürebileceklerini düşündüklerinden, tedarik zincirinin sağlamlığı etkilerden doğrudan olarak etkilenmemiştir. Ayrıca bulgular, risk yönetimi uygulamalarının aracı rolünü ve tedarik zinciri dayanıklılığını ve sağlamlığını geliştirmede oynadıkları önemli rolü ortaya koymaktadır.

Anahtar Kelimeler: Tedarik zinciri risk yönetimi uygulamaları, tedarik zinciri sağlamlığı, tedarik zinciri dayanıklılığı, COVID-19, salgın, CCA, PLS-SEM

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ABSTRACT

THE IMPACT OF SUPPLY CHAIN RISK MANAGEMENT PRACTICES ON PERFORMANCE DURING COVID-19 PANDEMIC

Lama ABDEL-RAHMAN

This study investigates the role of supply chain risk management (SCRM) in mitigating the effects of disruptions on the supply chain's (SC) resilience and robustness in the context of the COVID-19 outbreak. Even though few studies have been conducted in this field, it appears to have varying effects depending on the country and sector. With this motivation, data from 102 Turkish pharmaceutical firms are collected and analyzed using confirmatory composite analysis (CCA) based on partial least square structural equation modelling (PLS-SEM). The results of the hypothesis analysis show the negative impact of COVID-19 disruption on SCRM practices, SC resilience, and SC robustness, which demonstrates the negative impact of the epidemic on the practices of SCRM, and their abilities to regain their SC's performance after absorbing the disruption effects. COVID-19 appears to have a negative impact on how firms identify and control SC risks due to the amplitude of sudden global disturbances that few firms were able to predict in advance. The findings indicate that COVID-19 disruption impacts have mainly affected SC resilience. However, SC robustness was not directly affected by disruption impacts, as most of the firms seemed to think that they would be able to maintain their planned performance after the disruption. Furthermore, the findings reveal the mediating role of SCRM practices and the prominent role they play in fostering supply chain resilience and robustness.

Keywords: Supply chain risk management practices, supply chain robustness, supply chain resilience, COVID-19, epidemic, CCA, PLS-SEM

1. INTRODUCTION

A supply chain (SC) can be exposed to shocks and challenges that have impacted its performance over the years (Erhie et al., 2020). Recently, among other challenges, international restrictions on the Corona global epidemic have been implemented to ensure the safety of cities around the world; these have resulted in several services and production processes pausing and shutting down (Miroudot, 2020), causing some serious challenges via the SCs grid due to a decline in supply chain performance (SCP), and this decline appeared due to various reasons such as the mandatory absence of labor, product quality, and product safety. These had a significant influence on the suppliers' performance through a delay, besides other risks that caused a disruption (Ivanov & Das, 2020).

The rapid spread of the COVID-19 epidemic has resulted in the emergence of various global restrictions, which have resulted in a collapse in parts of SC performance, with disruption effects distinguished by their long duration (Araz et al., 2020). Consequently, the complete closure of several industrial production lines and some sectors have harmed the world's economy (Ivanov, 2020). Furthermore, several companies that have been harmed by the outbreak due to a lack of proper response needed to effectively employ RM strategies to deal with the consequences of the disruption. According to a study done on 1000 of the largest companies, more than 94 percent of the participating companies suffered from the negative impacts of the outbreak (Sherman, 2020).

Remko (2020) implies that the COVID-19 pandemic has had the maximum destructive impacts on the SCP through the past decades. So, effective risk management (RM) practices have been considered an important tool for developing survival mechanisms to mitigate the epidemic's threats by controlling the SC's performance, which is exposed to diverse risks. Usually, these practices are built on investing in suitable tools for contingency planning and mitigation practices (Ivanov et al., 2017). Researchers have sought to study the effects of disruptions on the SCP by measuring its resilience and robustness, which are considered performance outcomes, and it was created to mitigate threats to the SCP. Thus, the degree of importance attached to comprehending the SC's robustness and resilience has increased recently due to the high probability of risk exposure followed by disruption

impacts. In the context of the topic, the decision makers (DM) usually take actions to avoid risks and minimize their impacts through the implementation of suitable strategies to identify the potential risks and estimate the damages' degree before they can emerge, which reduces the vulnerability and ensures the processes' continuity. Those measurements in general are effective in enhancing SCP. Consequently, it is critical to investigate the approach taken by supply chain risk management (SCRM) to address the effects of the epidemic outbreak on the SC's performance.

According to Wieland and Wallenburg (2012), past researchers have significantly investigated SCRM practices. On the other hand, the linkages between SCRM's practices and SC's disruptions, resilience, and robustness have not been sufficiently investigated.

The main objective of this study is to investigate the role of SCRM's practices in mitigating the effects of disruptions' impacts on pharmaceutical supply chain performance (PSCP), including resilience and robustness measures in the context of COVID-19 epidemics. Secondary objectives need to be achieved to accomplish the main objective are:

1. Discovering the relationships among the proposed model variables: SCRM's practices, SC's disruptions, SC's resilience, and SC's robustness.
2. Investigating an empirical model based on the proposed conceptual framework.
3. Testing the framework for investigating the effective practices of the SCRM that would mitigate the COVID-19 disruption's impacts on SCP including its robustness and resilience.

Therefore, according to the previous objectives this study attempts to answer the following questions below:

Q1: Do COVID-19 affect supply chain risk management practices, robustness, and resilience of the supply chains of Turkish pharmaceutical companies?

Q2: Do supply chain risk management practices impact their supply chain robustness and resilience during the pandemic?

Q3: Can supply chain risk management practices mitigate the COVID- 19 disruptions' impacts on supply chain robustness and resilience?

In response to the preceding questions, the following hypotheses have been developed.

H1.a: Disruption impacts influence SCRM's Risk Identification (RI) practice negatively.

H1.b: Disruption impacts influence SCRM's Risk Assessment (RA) practice negatively.

H1.c: Disruption impacts influence SCRM's Risk Mitigation practice negatively.

H1.d: Disruptions' impacts influence SCRM's Risk Control (RC) practice negatively.

H2: SC's resilience is negatively influenced by Disruption impacts.

H3: SC's robustness is negatively influenced by Disruption impacts.

H4.a: SC's resilience is influenced positively by SCRM's Risk Identification practice.

H4.b: SC's resilience is influenced positively by SCRM's Risk Assessment practice.

H4.c: SC's resilience is influenced positively by SCRM's Risk Mitigation practice.

H4.d: SC's resilience is influenced positively by SCRM's Risk Control practice.

H5.a: SC's robustness is influenced positively by SCRM's Risk Identification practice.

H5.b: SC's robustness is influenced positively by SCRM's Risk Assessment practice.

H5.c: SC's robustness is influenced positively by SCRM's Risk Mitigation practice.

H5.d: SC's robustness is influenced positively by SCRM's Risk Control practice.

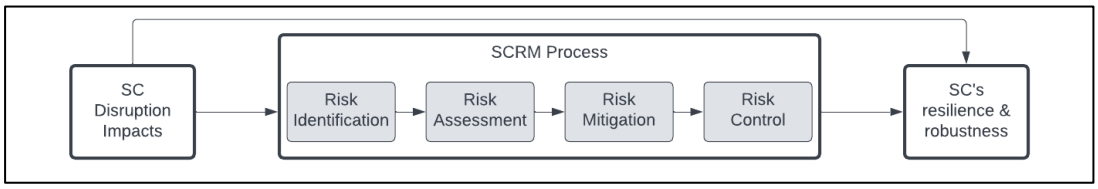

Figure 1.1: Interrelationship diagram detailed generic block flow diagram.

As a preconception of what investigation will disclose a combination of the proposed variables has been done to investigate the relationship between them, a simple generic block flow diagram is presented in Figure 1.1 This diagram represents the relationship between the connected block to be studied, it identifies the impacts of COVID-19 pandemic on the SCRM's practices and the SCP in direct relations and the impact of SCRM's practices on SCP during the disruption. SCRM's practices term

involves risk identification, risk assessment, risk mitigation, and risk control. And the SCP to be measured is its resiliency and robustness.

In this research, a quantitative approach was used to investigate the relationship between variables as shown in Figure 1.2 which represents the conceptual framework adopted by (El Baz & Ruel, 2020).

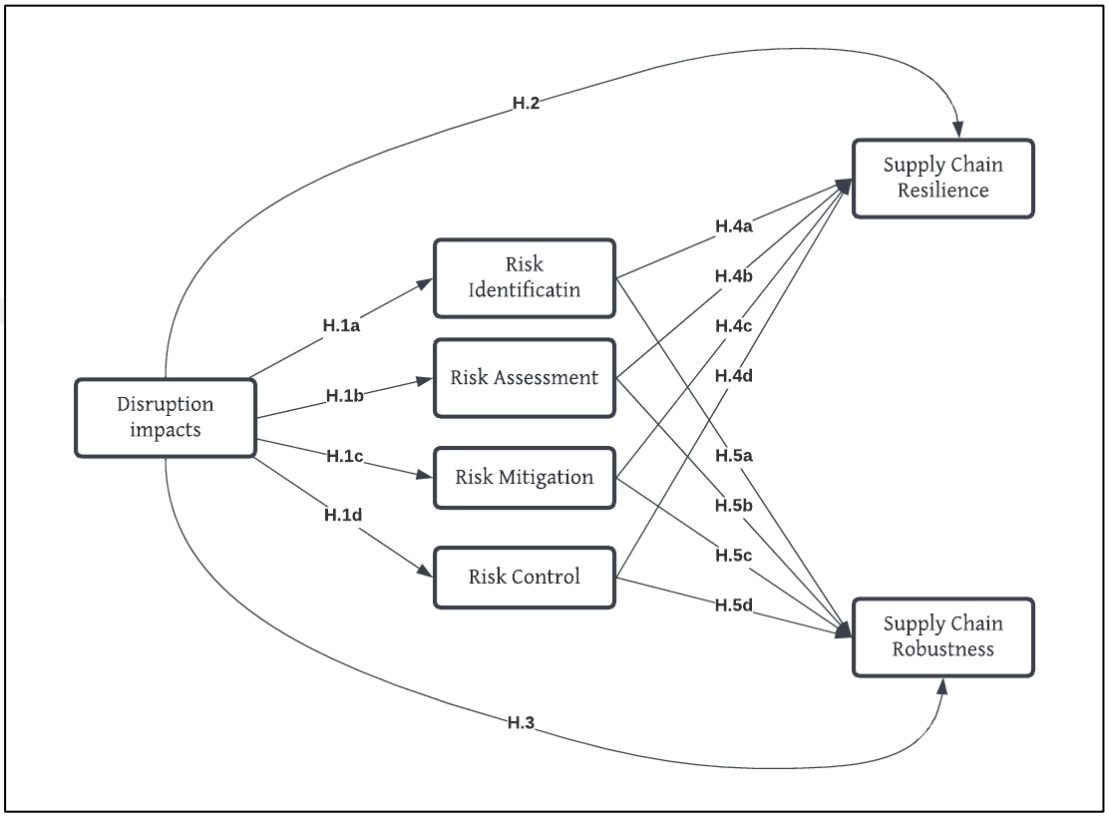

Figure 1.2: Conceptual framework.

Source: El Baz and Ruel (2020)

Indeed, researchers have proposed several models and the majority of them help in determining some proper strategies for helping various SCs around the world to deal with various risks. In this respect, the study is beneficial:

1. To hypothesize the relationship among SCRM's strategies and SCP, and then test the hypotheses with survey data by measuring its effect on the robustness and the resilience of the SC.
2. To find the effect of the implemented practices by the RM on pharmaceutical SCP during disruption.
3. To improve studies that investigate the role of SCRM practices on mitigating the disruption impacts on SC resilience (SCRES) and SC robustness (SCROS).

4. To test the consequences of a pestilence outbreak on SCP.

The thesis is coordinated as follows: The introduction shows a general outline of the current study by focusing on investigating the ability of SCRM's practices to mitigate the disruption impacts on pharmaceutical SCs' resilience and robustness in the context of COVID-19 epidemics as the field of the research topic, thus introducing a broad understanding to emphasize the importance of the topic clearly through demonstrating the aims of the study. Research questions are presented as well. Chapter 2 is the literature review, which gives an overview of the previous studies and shows the importance of the current research. Also, the framework implemented in this research is introduced. The research methodologies are presented in Chapter 3. In this chapter, the methods are discussed with more details about the survey and how it was conducted and analyzed using structural equation modeling using confirmatory composite analysis (CCA). Implementation and results in Chapter 4 give data analysis and numerical findings obtained. Chapter 5 is dedicated to recommendations and a conclusion. The main purpose of this section is to reflect on all the results and findings that have been found concerning the theoretical framework of the literature review as well as their possible contribution.

2. LITERATURE REVIEW

2.1. General Background about Supply Chain Management

Supply chain (SC) typically consists of units and subunits linked with each other through a group of commands and procedures coordinated in a hierarchical manner to continuously satisfy the demands of a variety of sectors, whether it be feedstock, products, services, or even information (Butilca et al., 2011). Juscius and Grigaite (2011) define the supply chain management (SCM) concept as a general association with the cascade of information, resources, services, and money through diverse activities. Typically, it is the management's responsibility to adjust their techniques when disruptions obstruct their performance and duties. As a result, new tools and techniques are being developed to ensure their resilience in the face of job disruption impacts. Figure 2.1 below shows that, in general, SC involves two or more distinct units linked by material, information, and financial transactions (Wisner et al., 2001). These entities might produce finished goods or raw materials, or they might provide logistical services (Stadtler, 2000). Therefore, the fundamentals of SCM presuppose a SC that follows processes from suppliers to end-customers (Croxton et al., 2001). The size, length, and complexity of SCs vary; Some firms will most likely have a short SC with only one supplier, while other firms have extended SCs.

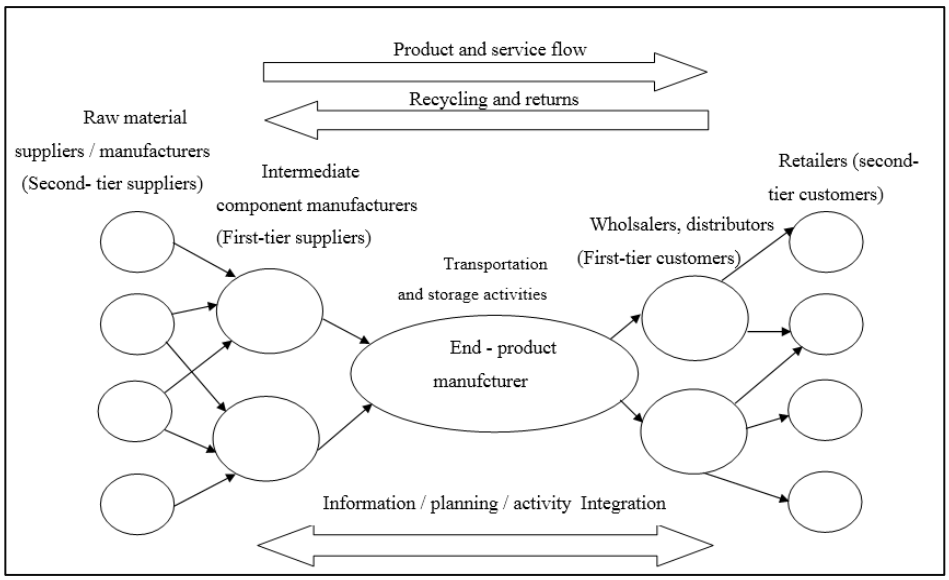

Figure 2.1: A general supply chain management model.

In the context of the development stages that have been experienced by most SCs around the world, undoubtedly, the majority of SCs did not begin their development stages until the 1960s. As a result, at the beginning of the 1960s, SC's systems in general focused primarily on inventory management and financial prescription, while later in the period between the '70s and the '90s, the focus of developments shifted to focus on client attraction and the continuity of product development, while now the focus is on the SC's process itself combined with the focus on customer satisfaction (CS) (Yousefia & Alibabaeib, 2015). Therefore, by improving the SC processes throughout, SCMs might be able to fulfil their objective of being more competitive (Stadtler, 2000; Tang, 2006).

Consequently, most SC is considered to play an important role in achieving the endeavours of business companies and also maintaining a high level in the competitive environment due to its important roles in meeting customer requirements, which include various actions applied to an integrated network of suppliers and manufacturing center management, beside controlling warehouses and a network of distribution points, and the retransmission of either raw materials or finished goods (Tuncel & Alpan, 2010). Furthermore, because of its crucial role in strengthening competitiveness, the new trend in competing is emerging amongst SCs rather than enterprises (Ritchie & Zsidisin, 2008). However, prevalent SC’s issues are frequently triggered by the levels of complexity of relationships among its components (Ganiyu et al., 2020).

2.2. Pharmaceutical’s Supply Chain

Initially, pharmaceutical industries are specialized in producing any substance or a combination of substances used for therapeutic, preventive, and diagnostic purposes in humans, each with a different manufacturing process, as published in the Official Journal of the European Union (2001). And in order to secure raw materials, they collaborate with a variety of industries. Over time, the world's reliance on pharmaceuticals to protect human health has increased steadily. Moving on to SC details, a pharmaceutical SC's processes typically include the production of raw materials as the first step, followed by shipping the raw materials from their suppliers' source to the pharmaceuticals' production lines, and finally the distribution of the final

products to consumers via distribution centers to retail. pharmacies, hospitals, and patients. Figure 2.2 below illustrate the components of pharmaceutical's SC (Aich et al., 2019).

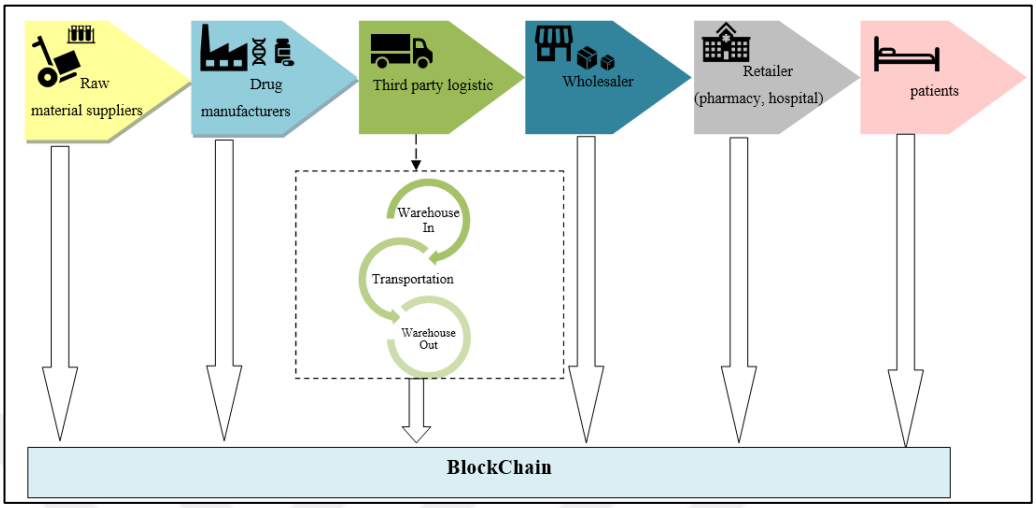

Figure 2.2: Pharmaceuticals SC's components.

Continuing on the types of drug suppliers, according to the size and capacity of the company, drug suppliers are generally divided into two categories: generic drugs and branded. According to research, generic companies are more sensitive to SC risk than branded companies, due to lower earnings and the fact that they rely more on external suppliers. Figure 2.3 describes the difference in the degree of vulnerability for the generic and the branded pharmaceuticals' SC (Jung et al. ,2020).

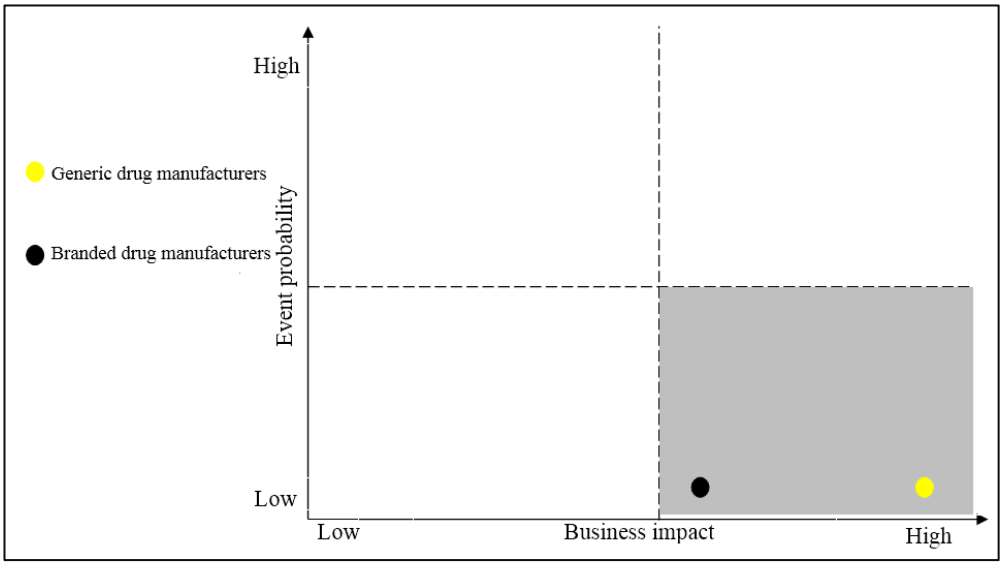

Figure 2.3: Implications of COVID-19 on pharmaceutical's supply chain.

Accordingly, the PICK chart above describes the effects of COVID-19 on the pharmaceutical industry's SC, where the black spot represents the branded drug manufacturers, and the yellow represents the generic drug manufacturers, with business impact on the x-axis and event probability on the y-axis. As demonstrated, generic drug manufacturers are vulnerable to pandemics such as COVID-19 due to lower profit margins and a greater reliance on other productive countries for supply. On the contrary, it is the opposite for branded companies. Even though companies need to rethink whether their current models can manage the risks associated with low-probability and high-impact events (HILP).

Pharmaceuticals' supply chain risk management (SCRM) system has recently been considered to play a crucial role in managing risk and preventing delays to ensure products' distribution to the final customer. First, in this context, it is relevant to emphasize the vulnerability points in pharmaceuticals' SC that are most vulnerable according to the literature. Accordingly, Figure 2.4 below explains the areas of potential disruption throughout the pharmaceutical industry's SC **(**Jung et al.**,** 2020**)**. Active pharmaceutical ingredients (APIs) are substances that are used in the production of pharmaceuticals, and usually the essential ingredients in the production of APIs are basic and intermediate chemical components. Consequently, the availability of the final products relies mainly on having access to secure APIs, which are usually produced in certain countries; thus, the needs for packing and shipping could cause an unexpected disruption.

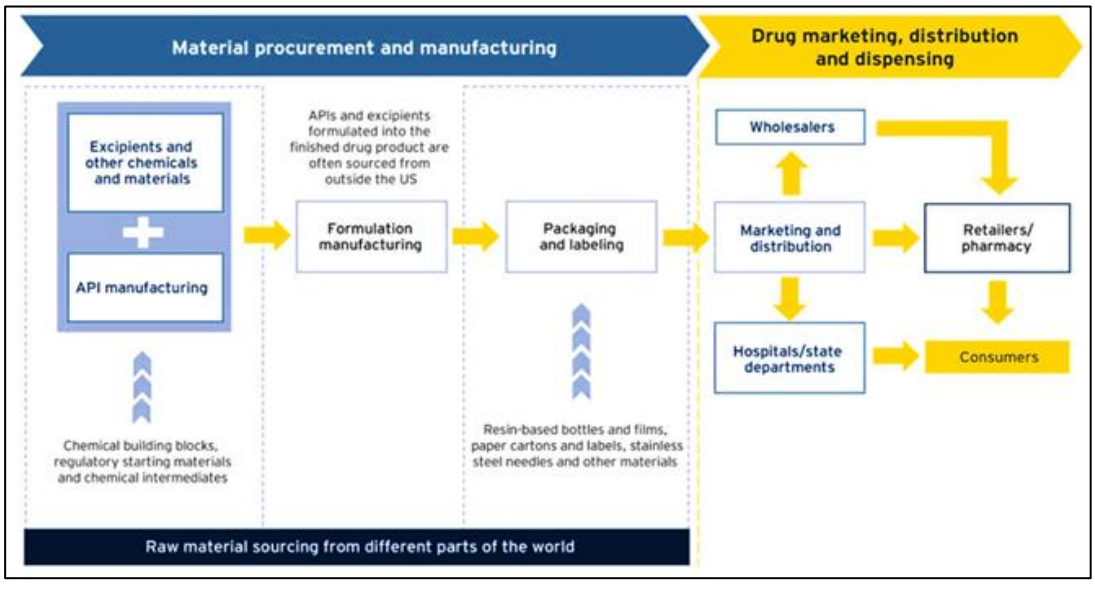

Figure 2.4: Pharmaceutical supply chain: area of disruption and interruption.

The indicators shown in the graph suggest that disruption of any connected component in the pharmaceutical supply chain could lead to potential drug delays. Furthermore, manufacturers' reliance on sporadic raw material supplies for drug APIs, excipients, and formulations, as well as packaging and labelling, can lead to production and supply bottlenecks.

It is necessary to examine the supply chain risk indicators to understand the current damage situation of the pharmaceutical SC company. For example, economic indicators for pharmaceutical companies and the impact of disruptions in the supply chain on pharmaceutical companies.

Regarding the economic situation of Turkey, the World Economic Forum's Global Competition Index (2020-2021) ranked it 61st out of 140 competitive countries in the world (World Economic Forum, 2021). The pharmaceutical sector, in particular, is regarded as a driving force in supporting Turkey's health and economic goals. Consequently, the Turkish pharmaceutical market was the world's 18th largest in 2020 and ranked 27th in the pharmaceutical export ranking (Türkiye Istatistik Kurumu (TUIK), 2020).

Figure 2.5 from TURKSTAT (2021) shows that pharmaceutical exports in 2020 increased compared to the previous year, particularly after August. In 2020, total pharmaceutical exports increased by approximately $1.8 billion over the previous years. Exports fell by 1.7% from January to July 2021 compared to the size of exports in the same period last year.

In general, most of the pharmaceutical companies in Turkey import their majority of raw materials, some active ingredients, and drugs that are not feasible to produce in Turkey. According to statistics, pharmaceutical imports increased by 3.7% in 2020 compared to 2019, with a value of approximately $5.5 billion in imports, while exports increased by 38% with a value of about $1.8 billion, resulting in a negative trade surplus because exports were less than imports and the ratio of exports to imports was 32%. As a result, the market has grown compared to the previous year, reaching sales of around 47.9 billion Turkish Liras in 2020.

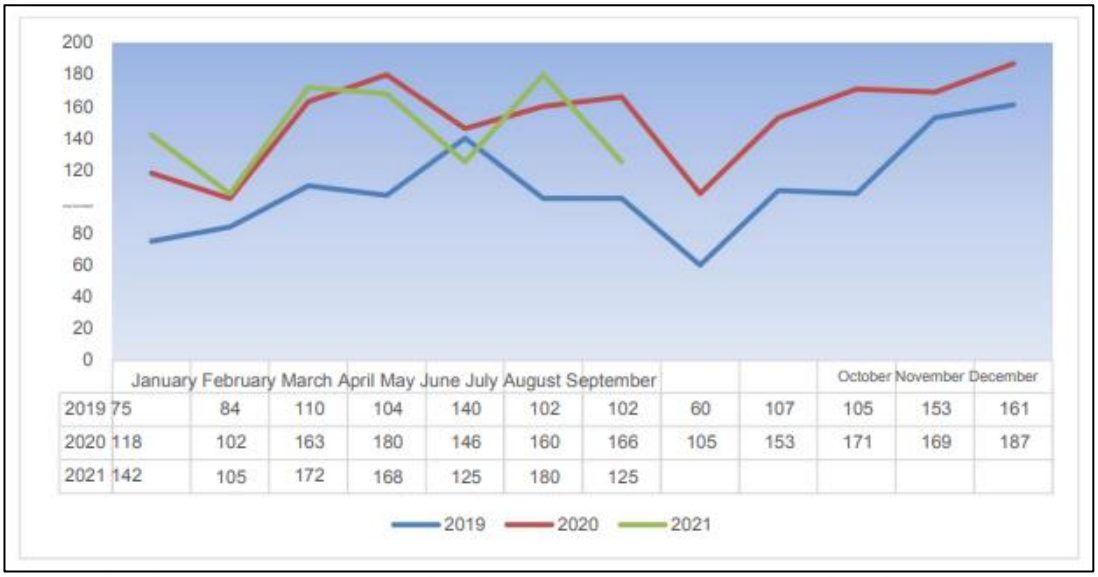

Figure 2.5: Monthly export assessment (Million USD).

Figure 2.6 shows that in 2019, the foreign trade deficit reached $4 billion and decreased to approximately $3.7 billion in 2020. Economically, as a rule of thumb, if the foreign trade balance favours imports, it will contribute to prosperity in the pharmaceutical sector (TUIK, 2020).

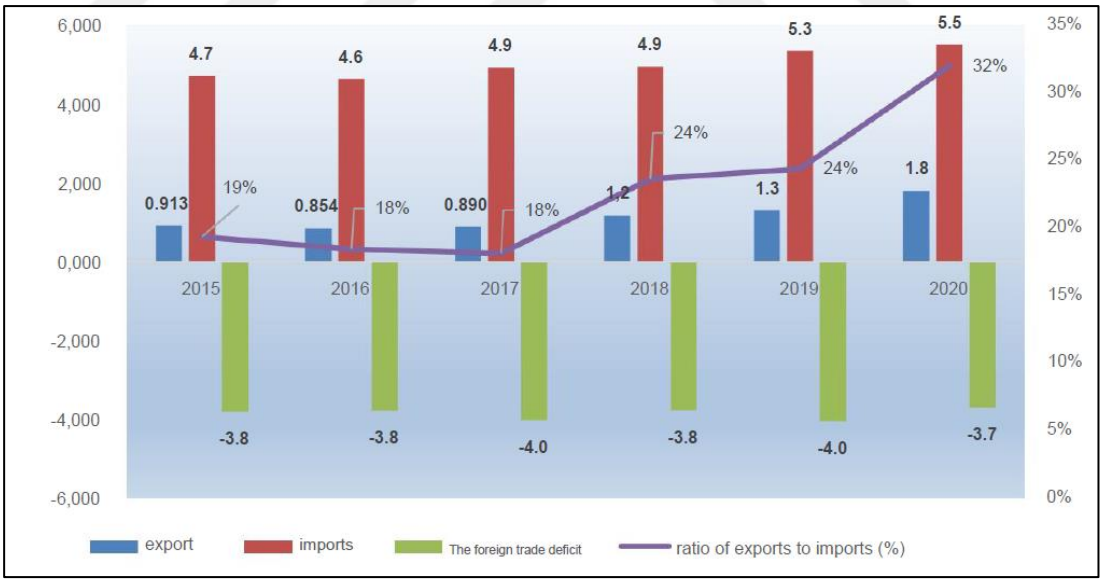

Figure 2.6: Industry imports and exports (Billion USD).

According to the literature, the Turkish pharmaceutical sector produces several APIs, especially antibiotics and analgesics, under license, contract manufacturing, and generic drug production (T.C. Sanayi ve Teknoloji Bakanlığı, 2021). Accordingly, in 2020, Turkey manufactured on a box basis approximately 1.94 billion boxes of

pharmaceuticals for the Turkish market, which on a value basis reached about 24.3 billion TL (T.C. Sanayi ve Teknoloji Bakanlığı, 2021). However, some medicines are only produced in particular centers worldwide, as they require advanced technology. Consequently, Turkey does not manufacture some drugs with low consumption and unprofitable production. In 2020, the capacity utilization rate decreased compared to the previous year and averaged 69.9% (T.C. Sanayi ve Teknoloji Bakanlığı, 2021).

Analyzing the distribution of the Turkish prescription drug market in terms of value (TL) as of 2020, results show approximately 68% of the market is innovative drugs, and 32% of them are equivalent drugs (T.C. Sanayi ve Teknoloji Bakanlığı, 2021). Furthermore, as Figure 2.7 provides a clear comparison of the import assessments for three different years in the pharmaceutical sector in Turkey, the pharmaceutical imports in 2020 increased by 4% compared to the previous years and reached approximately 5.5 billion dollars. Imports increased by 36% from January to July 2021 compared to the size of the pharmaceutical imports in the same period last year (T.C. Sanayi ve Teknoloji Bakanlığı, 2021).

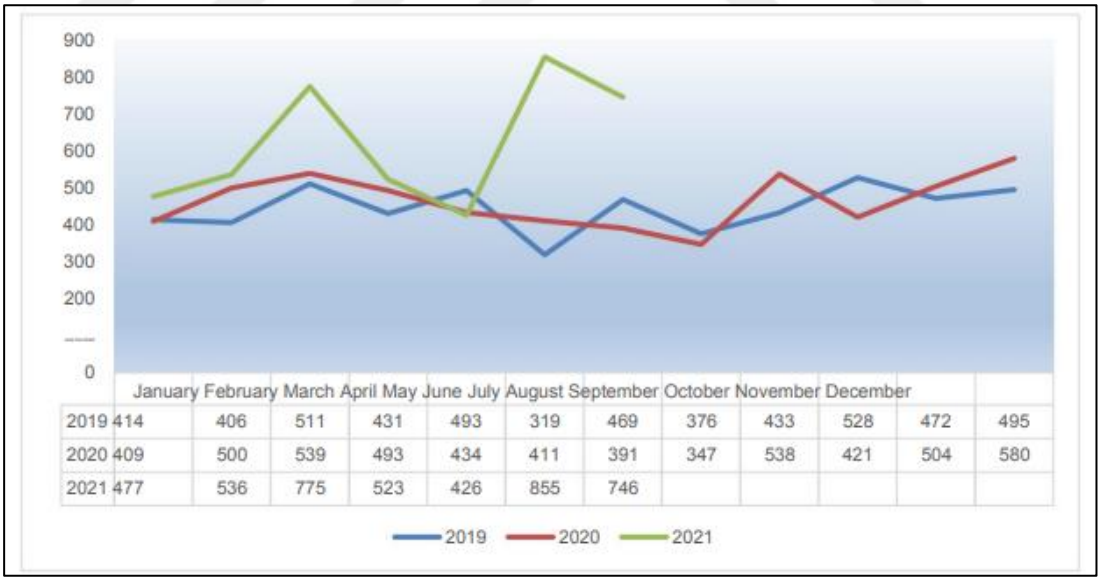

Figure 2.7: Monthly import assessment (Million USD).

According to the SGK 2020 data, the number of enterprises that carry out the production of active pharmaceutical products and the manufacturing of pharmaceutical medicines is 637 in Turkey, and the number of employees is approximately 31,899. Almost all of the companies in the sector operate in the province of Istanbul and the

surrounding. Factors such as the more suitable infrastructure, the convenience of supplying packaging materials and technical personnel, the transportation and communication facilities, and the concentration of health institutions in the Marmara Region have led to the establishment of a large portion of the pharmaceutical companies in the province of Istanbul.

According to TUIK data for 2020, the production value of "Manufacturing of Basic Pharmaceutical Products and Pharmaceutical Materials" is approximately 39.8 billion TL. Based on 2015, the industrial production index value in "Manufacturing of Basic Pharmaceutical Products and Pharmaceutical Materials" showed a regular increase, especially after 2013, and reached its highest value in 2020. The incentives applied for the development of the pharmaceutical industry are considered to play an important role, especially in 2013 and later, as Figure 2.8 shows.

In this context, the SC of the pharmaceutical industries in Turkey is typically similar to that of other SCs, consisting of an integrated system that includes all stages, beginning with R&D department processes and ending with the shipment of medications to the final consumer, which in this case is the patients at hospitals or retail pharmacies.

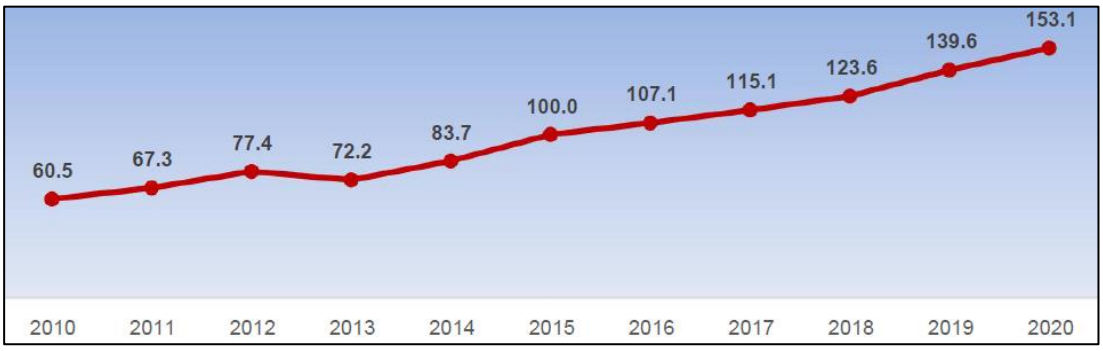

Figure 2.8: Industrial production index for pharmaceutical products in Turkey.

Manufacturers typically manage the actual distribution of drugs from producers by controlling the supply process of goods from manufacturing plants to wholesalers (Datex, 2018); the wholesaler is usually considered the majority of purchasers. Thus, the stakeholders in this integrated network include pharmaceutical manufacturers, R&D companies, pharmaceutical distributors, wholesalers, government health agencies, hospitals, insurance companies, pharmacy retail stores, and patients (OCED, 2000). As shown in Figure 2.9, suppliers typically provide lab equipment, raw

chemicals, and R&D software for pharmaceutical manufacturing plants to enable the companies in the R&D stage to perform their tasks more comfortably (Erhie et al., 2011). Once the development process is complete, the next step is to start manufacturing drug batches. Producers usually subcontract with third-party logistics to get APIs to produce finished goods. Constant quality control (QC) and monitoring checks are performed on the assembly lines as well as the batches to prevent improper labelling of the final products, and then the finished products are packaged and labelled before they are delivered and dispensed.

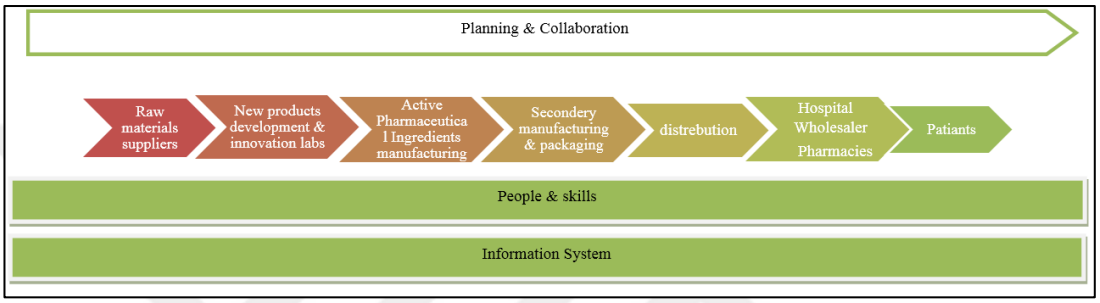

Figure 2.9: The general stages of pharmaceutical's SC.

Furthermore, as illustrated in Figure 2.10, although the local production of the Turkish pharmaceutical industries has declined over time, the reason is usually attributed to the industries' tendency to import API to reduce manufacturing costs by a reasonable percentage, but the majority have been able to emerge in the pharmaceuticals' R&D and record a higher percent in the local production (Erhie et al., 2011). In general, managing the pharmaceutical industry's SC is challenging because of its complexity and the government regulations in this field (Yousefia&Alibabaeib, 2015).

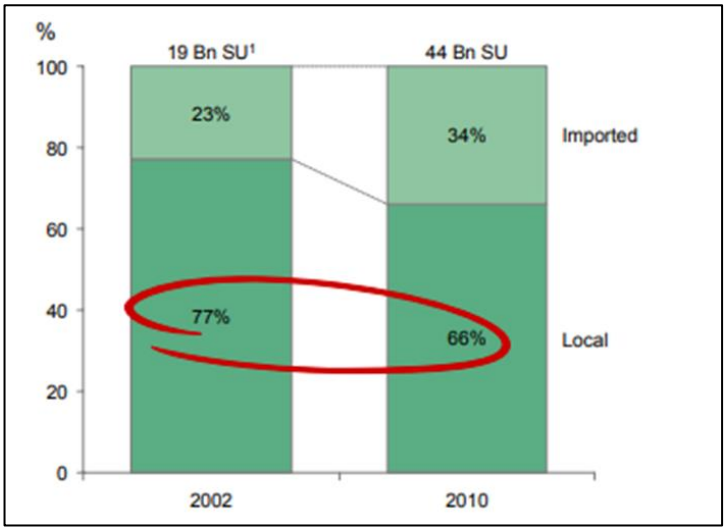

Figure 2.10: The general stages of pharmaceutical's SC.

The COVID-19 epidemic has heightened the frequency of risks that disrupt and cause insecurity in the pharmaceutical industry's supply chain. Hence, the average demand for pharmaceuticals has increased due to the interruptions caused by COVID-19 circumstances, which caused goods to run out of stock.

Researchers claimed that disasters no longer have a local impact since they affect global manufacturers and suppliers in various sectors through the network, hence, have a higher probability of negatively impacting the performance of several SCs. Therefore, one of the biggest business problems today is the management of disruptions via SCRM (Blackhurst et al., 2005).

Furthermore, the COVID-19 pandemic has adversely affected all stakeholders in the value chain, from suppliers to customers. Accordingly, the spread of the virus has severely affected the global SC network. Due to logistics problems and transportation restrictions, raw materials and finished products are not supplied on time, and several production lines are closed or operating at a lower capacity (Zuo et al., 2021). Therefore, the importance of local production in the pharmaceutical sector reflects positively on the economic performance indicators.

Indeed, the Turkish pharmaceutical industry is an industry with a deep-rooted history and high production capacity provided by advanced technology. The extraordinary conditions imposed by the COVID-19 pandemic process, which started in China at the end of 2019, have affected the whole world and the pharmaceutical industry in Turkey as well (T.C. Sanayi ve Teknoloji Bakanlığı, 2021).

2.3. Supply Chain Risks

Generally, Oxford Dictionary defines risk as a situation involving exposure to a hazard. In other words, the deviations from the usual outcomes, whether desirable or not (Williams et al., 1998). Several researchers have considered the probability of getting undesirable results as a risk (Supply Chain Risk Leadership Council, 2011). Regarding risks associated with SC, they usually appear as disruptions (DuHadway et al., 2019), which denote the possibility of an event occurring in the future (Waters, 2011). Manners-Bell (2014) divides risks into three groups as follows:

1. Recognized and ready to deal with: These are events that have occurred in the past and are likely to occur in the future.
2. Recognized and not ready to deal with: These are events that have happened frequently in the past, but governments and corporations were unprepared to find solutions to deal with them.
3. Not recognized and not ready to deal with: They are difficult to predict, but they have the potential to cause significant damage.

SCs have historically faced several types of risks that put their organizational targets in danger and resulted in failures in their operations. Thus, the definition of supply chain risk (SCR) is the probability of losing the efficiency and effectiveness targets of a SC as a result of exposure to a disruption event (Heckmann et al., 2015).

Several approaches have been followed in the literature and have helped in the process of SC risk (SCR) classification:

Zsidisin (2003) has classified SCRs based on their source and outcomes. Sources fall into two categories: individual supplier failures, such as failed shipments, poor relationships, and quality issues; and market characteristics, such as limited qualified sources and market shortages. However, the outcomes are classified as a failure to satisfy the customer's needs, such as missed deliveries, and risks to client life and security, such as product liability.

Spekman and Davis (2004) identified three possible sources of risk in SC: material, financial, and informational flows, which could be affected by information security, SC partner relationships, and corporate social responsibility. As a result, any point along any SC could be a potential source of risk. Juttner et al. (2003), also built

the classification of SCR based on its sources as environmental, network, and organizational risk sources.

Waters (2011) distinguishes between internal and external risk sources; internal SCRs could arise from daily operations whereas external SCRs appear from the outside environment attacking SC operations. Juttner et al. (2003) have mentioned three sources of SCRs: supply, demand, and the environment.

Chopra and Sodhi (2004), Tang and Tomlin (2008), and Manuj and Mentzer (2008) have proposed their classifications based on supply and demand risks. Wagner and Bode (2006) have also distinguished between the demand side, supply side, regulatory, legal, and bureaucratic, infrastructure, and catastrophic.

Oke and Gopalakrishnan (2009) classified SCR types based on the degree of impact and the frequency of risk occurrence. Chopra and Sodhi (2004) have provided a comprehensive list of SCR categories such as disruptions, delays, systems, forecast, intellectual property, procurement, receivables, inventory, and capacity.

Xu et al. (2020) have classified the SCR types as operational and disruption risks. Operational risks (OR) are predictable and interrupt the smoothness of SC's operations. On the other hand, disruption risks (DR) are unexpected events that have massive impacts, such as crises (Kinra et al., 2019).

COVID-19 crises represent a distinct type of SCR that may have a disruptive effect on the resilience and robustness of the SC from the financial, economic, social, ecological, and political perspectives (Ivanov, 2020). SC disruptions could take various forms, ranging from a transportation delay to a natural disaster or a terrorist attack (Blackhurst et al., 2005). They could harm supply chain performance (SCP) by increasing costs, failing to fulfill consumer demand, and causing stock-outs. Usually, the term "ripple effect" describes how the impacts of such occurrences propagate across the SC (Ivanov et al., 2014).

Due to the disruption circumstances, in this study, the classification of SCRs has been adopted from the literature and proposed by Juttner et al. (2003), who declared that the environmental risk sources are uncertain events that appeared from the surrounding environment and interacted strictly with the SC's operations at all stages, whether they occur due to accidents, socio-political actions, or natural disasters.

In conclusion, A wide range of risks might affect the SC network, and the SCR can have an insignificant impact on the firms' performance (Svensson, 2000). SCM plays a vital role in a company's ability to meet consumers' demands since SCRM is a term for managing the risks related to the SC, to ensure profitability and sustainability (Tang, 2006b).

2.4. Supply Chain Risk Management

Supply Chain Risk Management (SCRM) is defined as the process of identifying and implementing essential treatments or mitigation activities to address identified risks (Behdani, 2013). As a result, it is a fundamental tool that frequently employs proactive and reactive precautionary measures to confront the contributing variables that cause chain fragility and vulnerability.

The approach of SCRM is based on an effective investigation of the fragile aspects of the chain and forecasting the sources of potential risks, and hence the reporting of the consequences of these specific risks, all of which take place prior to the accident. These approaches would provide a fertile statistical environment that would assist in the decision-making process and thus reduce the damage caused by changes or prevent them (Ergun et al., 2010).

Typically, SC operations are affected by various interrupts. In general, several companies are following traditional methods to avoid risks in an inefficient way, therefore losing their competitive advantage. Usually, the challenge is maintaining profits while reducing the probability of risks occurring that disrupt SC's operations. Thus, according to the brief discussion, RMs usually assess the factors that affect competitive values, profits, and corporate goals. So, risk management (RM) seeks to achieve competitive values by building resilience plans for the SC's processes (Katsaliaki et al., 2021).

Vulnerability reflects a SC's susceptibility to disturbance (Waters, 2011). Because SCs are becoming more vulnerable, building a resilient SC via SCRM is becoming increasingly critical. According to the definition, resilience means the system can return to its original condition or move to a different, more desirable state after being disrupted. The robustness of SC is defined as a system's ability to cope with errors (Christopher & Peck, 2004) or as a system's ability to tolerate or survive external

shocks (Lempert et al., 2010). When dealing with risks and disruptions, both are considered crucial.

SCRM is considered an entity responsible for effective risk management that generally deals with risks, its practices summarized through the following procedures: it begins by identifying the direct risks that threaten the smoothness of its operations, taking into consideration the potential causes and sources of risks; the next step is to take appropriate precautions to avoid the chain's vulnerability. This continuous enhancement of the SCP gives firms competitive value and helps in process development. Thus, as a result, SCRM practices attempt to minimize the impact of fragility and disruption (Ho et al., 2015). By establishing certain practices (Fan & Stevenson, 2018), one can face the influences of SC disruptions, which impede the smoothness of material and information exchange operations in general SC (Chowdhury & Quaddus, 2017).

Consequently, SCRM practices are an important indicator of SC success since they have positive effects on SCP (Narasimhan & Talluri, 2009). Fluctuations in SC generate a sequence of responses to sustain the SC's goals. Charkhab et al. (2014) notice the necessity to apply proactive and reactive methods as an effective strategy to deal with SCRs.

In general, most RMs develop their ability to predict the occurrence of risk through a thorough understanding of the variables in the surrounding environment and within the chain that contributes to success in achieving the planned goals. On the other hand, a failure in risk management leads to disruptions in both goal achievement and task completion. Therefore, a deep understanding might help in providing methodologies to mitigate damages and take actions to avoid risks (Charkhab et al., 2014). Rao and Goldsby (2009) identified risk mismanagement as the first cause of SC deterioration.

Sodhi et al. (2012) has identified four key elements for managing SCRs. These elements are:

1. Risk identification

2. Risk assessment

3. Risk mitigation

4. Responsiveness to risk incidents.

Given this, their identification demonstrates that Sodhi et al. (2012) do not make the same distinction as Behdani (2013) and have combined pre- and post-disruption management as an integrated process within SCRM. In addition, considering SC-disruption management actions, these can be divided into three categories using the concept of pre- and post-disruption views (Blackhurst et al., 2005):

1. Disruption discovery
2. Disruption recovery
3. SC redesigns

Pyke and Tang (2010) have expanded on an integrated approach to risk management, as have Sodhi et al. (2012). Their strategy is divided into three stages: readiness, responsiveness, and recovery, as Figure 2.11 below shows.

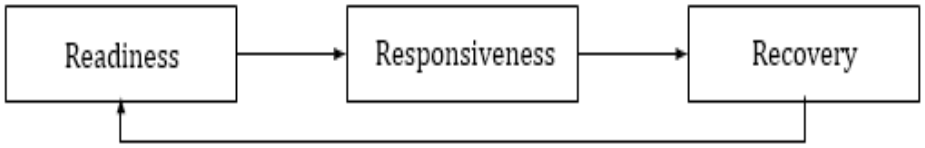

Figure 2.11: The 3R framework for mitigating product recall risk.

This study aims to focus on the following SCRM practices, which involve risk identification, risk assessment, risk mitigation, and risk control. These steps equip managers with strategic information to select strategies that mitigate different risks to improve the overall performance of the SC, as Figure 2.12 below shows (Behdani, 2013).

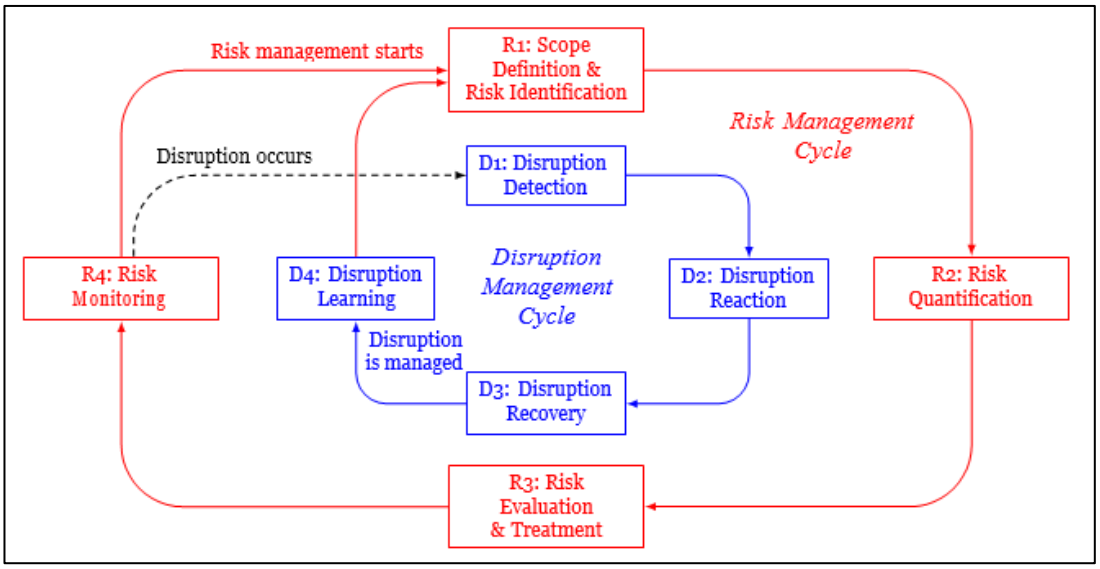

Figure 2.12: The integrated framework for managing disruption risks in supply chains.

During the RI stage, risks that the SC may face are detected. Next step is RA which determines risks that would impact a SC vulnerability. The prioritization of risks is an essential element of SCRM since it allows the organization to concentrate its decision-making. In risk mitigation stage, SC managers usually execute strategies that help in mitigating the disruption effects. Finally, the RC risks are monitored frequently. Thus, SCRM is considered a rapidly growing field that aims to create ways for the assessment, mitigation, and control of areas of vulnerability and risk in SCs (Neiger et al., 2009). The following sections describe four components of the SCRM practices in detail.

2.4.1. Risk Identification (RI)

The initial step in eliminating errors that occur within the SC environment is to establish identification procedures for risks and detect them. That implies the early recognition of the likelihood of risks as a factor in minimizing the severity of the SC interruptions, which necessitates accurate identification of the sources of risks (Chowdhury & Quaddus, 2017). The pandemic cycle typically begins with the early stages of identification. Hence, this phase is considered the basic building block in SCRM practices to achieve optimum utilization and improve the level of efficiency of screening (Wieland & Wallenburg, 2012).

Ivanov and Dolgui (2020) discuss the importance of contributions that can be found in identifying disruption scenarios and critical nodes, the failure of which would lead to SC discontinuities and operational collapse.

According to Yildiz et al. (2016), the decision on risk identification in the early stages is aimed at the implementation of resilience-building SC.

Accordingly, based on the previous arguments and considering the various SCRM practice RI, the current study search tests the following hypotheses:

H1.a: Disruption impacts influence SCRM's Risk Identification (RI) practice negatively.

H4.a: SC's resilience is influenced positively by SCRM's Risk Identification practice.

H5.a: SC's robustness is influenced positively by SCRM's Risk Identification practice.

2.4.2. Risk Assessment (RA)

The second step in the RM cycle is the evaluation of the predicted impact of a given SCR. Despite the risk, SCRM works to keep the objectives met. This step is typically completed by assessing performance indicators (Behdani, 2013); thus, it provides the SCRM with the ability to select management actions that are appropriate for the situation. According to Wieland and Wallenburg (2012), RA includes a computed estimation and an identification of the most vulnerable points in the SC, which, as a result, provides a fertilized database of information on the sources of risks and accurate information about risk impacts and weakness points. Furthermore, the duration of the risk is used to determine the intensity of the risk. Conversely, the risk caused by disruptive events is challenging to analyze; thus, those disruptive events in supply chain management have a negative influence on the performance of supply chain management processes (Xu et al., 2020). Moreover, by considering possible occurrences of events, risk management assessment complements the resilience supply chain (Aven, 2017).

Kleindorfer and Saad (2005) imply the principle that investments in RA to determine key vulnerabilities are a critical first step in disruption risk management and that mitigation plans for responding to worst-case scenarios are of relevance in prioritizing mitigation strategies.

Based on the previous arguments, and considering the various SCRM practice RA, the current study tests the following hypotheses:

H1.b: Disruption impacts influence SCRM's Risk Assessment (RA) practice negatively.

H4.b: SC's resilience is influenced positively by SCRM's Risk Assessment practice.

H5.b: SC's robustness is influenced positively by SCRM's Risk Assessment practice.

2.4.3. Risk Mitigation

The third step of the risk management cycle is considered an early stage, which is before the occurrence of interruptions. Then, risk managers employ a series of appropriate perpetration strategies to mitigate the harms caused by those risks (Azadegan et al., 2020). According to Fan and Stevenson (2018), usually, there are several factors affecting the efficiency of risk mitigation, such as the degree of responsibility of SCRM practices and the degree of integration among the SC. The rate of responsiveness for SC partners should be quick to reduce the disruption impact because most risk mitigation activities are presumed to take a long time to be completed due to their strategic nature, providing decision-makers the opportunity to collect additional details and arrive at a near-optimal solution (Datta & Christopher, 2011). According to the "ripple effect," disruptive events harm each subsequent link of the SCM system (Ivanov et al., 2014).

Kleindorfer and Saad (2005) discuss schemes that help to detect and mitigate risks while increasing the level of readiness and preparedness to respond to risk. Garvey and Carnovale (2020) argue that management should focus more of their attention on the control or mitigation of exogenous events. Wieteska (2020) stated that there is a positive correlation between a company's risk mitigation and achieving SC resilience. Geers et al. (2021) stated that mitigating the negative effect of SC disruption would positively be reflected on companies' robustness.

Based on the previous arguments, and considering the various SCRM practice risk mitigation, the current study tests the following hypotheses:

H1.c: Disruption impacts influence SCRM's Risk Mitigation practice negatively.

H4.c: SC's resilience is influenced positively by SCRM's Risk Mitigation practice.
H5.c: SC's robustness is influenced positively by SCRM's Risk Mitigation practice.

2.4.4. Risk Control (RC)

The final step is after risk managers implement mitigation actions. The RC step entails reducing the likelihood and severity of risk occurrence by implementing developed systematic strategies (Wieland & Wallenburg, 2012). Usually, RC strategies should be adopted by an organization with an active attitude toward controlling and re-evaluating SCRM permanently. In general, protecting an organization from risks is difficult; therefore, it should be observed (Behdani, 2013). In the history of business, there have always been unpredictable events that have negative effects on the risk management system (Kiebler et al., 2020).

Based on the previous arguments, and considering the various SCRM practice RC, the current study tests the following hypotheses:

H1.d: Disruptions' impacts influence SCRM's Risk Control (RC) practice negatively.

H4.d: SC's resilience is influenced positively by SCRM's Risk Control practice.

H5.d: SC's robustness is influenced positively by SCRM's Risk Control practice.

2.5. Supply Chains Robustness and Resilience

SC resilience (SCRES) and SC robustness (SCROS) are considered performance outcomes, and they mitigate threats to SCP. Several studies have proven the effectiveness of resilience and robustness in maintaining the expected level of the SCP (Dolgui et al., 2020). As a result of the high likelihood of risk exposure followed by disruption impacts, understanding the SC's robustness and resilience has recently increased in importance. Concerns about the disruption of SC processes grew as the Corona epidemic spread, necessitating an urgent need to ensure the growth and continuity of SC processes; this has created pressures to investigate the impact of RM practices on the resilience and robustness of the SC during epidemic period to provide decision-makers with methodologies that could be used later in similar circumstances (Ivanov, 2020).

Researchers have developed several definitions for the robustness and resilience of SC. Resilient SC is the ability to respond to sudden disruptions with subsequent restoration of the standard normal operational states by accepting temporary setbacks and focusing on recovery in a specific period after risk exposure (Simchi-Levi et al., 2018). Thus, it implies that the disruption harms the SCP but that it can restore normal conditions. Hence, it achieves its purpose by shifting toward desired states to avoid failure modes (Carvalho et al., 2012). On the other hand, robustness is the capability of the SC to resume its initial performance level following disturbances, and it commonly requires changes to maintain effectiveness.

Figure 2.13 shows the difference between optimal and robust plans. There are two distributions: the green line distribution represents the optimal plan, while the blue line represents the robust plan. This chart studies the quality of the plan concerning safety time. As the results show, when risk managers face disruptions, applying their optimal plan will provide a high-quality plan, but it is more fragile in terms of the assumed safety time; therefore, robust plans are more suitable to deal with the disruptions.

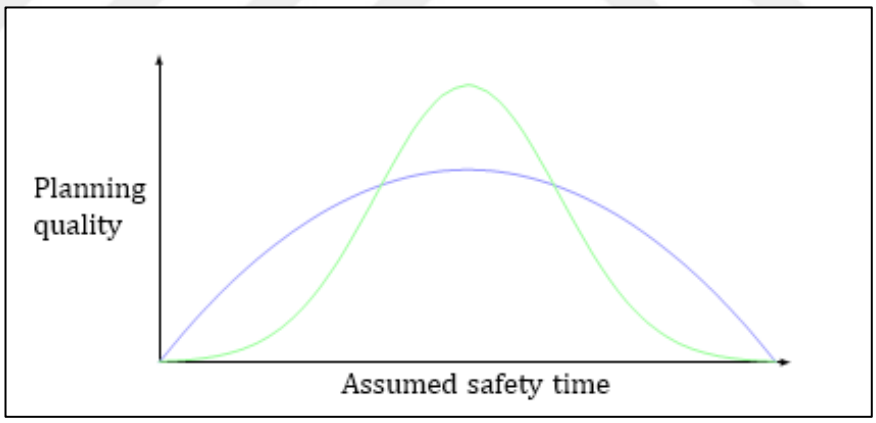

Figure 2.13: Robust vs optimal planning.

Thus, organizations have figured out how to improve the resilience and robustness of their global SCs in the face of severe calamities. However, COVID-19 has emerged as a new stimulator of SC disruption, unlike any other in recent times. So, several organizations have invested in risk mitigation inventory, subcontracting capacities, backup supply, and transportation infrastructures, and data-driven, real-time monitoring, and visibility systems have strengthened SCRES (Ivanov, 2017; Xu et al., 2020; Dolgui et al., 2020).

Ivanov and Dolgui (2020) discuss the importance of measuring SC robustness and resilience under disruption propagation and propose ways to enhance resilience, such as supplier diversification. Juttner and Maklan (2011) find that the data analysis revealed that the resilience capabilities helped the companies to contain the negative effect of the disruption impact. Also, they declare that the literature suggests that SCRES is coupled with dynamic capability, which enables absorbing the negative effects from several risk sources.

Figure 2.14 shows the importance of SC resiliency. The V_3 curve represents resilient SCs because these systems are distinguished by early detection of the risk event and rapid response, allowing for a quick return to the SCP with minimal damage impacts. On the other hand, systems that suffer from a lack of SCRES discover the risks in delayed time, leading to a delay in the response to the risk events and causing a drop in the performance of the SC system, such as in the V_1 and V_2 curves, which indicate the degree of decline from the normal rate of performance (V_0). To summarize the importance of SC resilience, consider the following:

1. Reduce the time and duration of the event.
2. Reduce severity and the slope of the event.
3. Accelerate the time to recover.

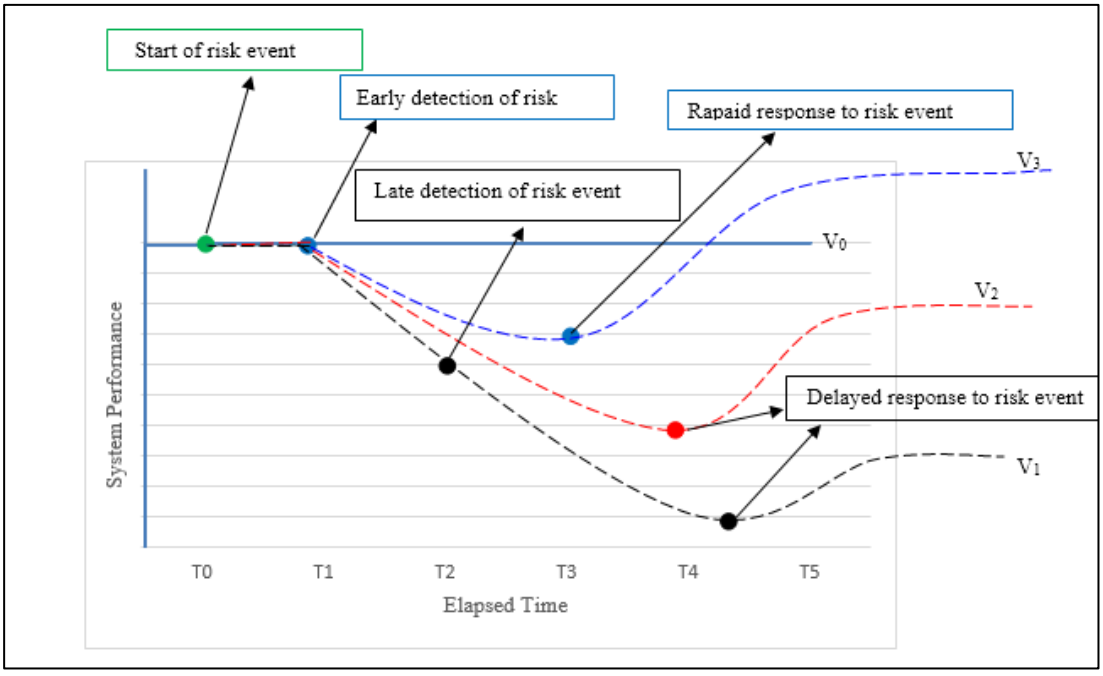

Figure 2.14: Risk event detection and response.

An example of a resilient supply chain is Toyota's ability to resume manufacturing at 29 of its factories four days after the Kobe earthquake of 1995 (Fujimoto, 2011). While an example of a strong supply chain, Li and Fung kept their customers supplied during the Indonesian currency crisis when many of their competitors had to halt production (Tang, 2006b). As a result, several companies, including Coca-Cola, Cisco, and Boeing, are working with their SCs to build robustness and resilience (Brandon-Jones et al., 2014).

Based on the previous arguments, and considering the SC's robustness and resilience, the current study tests the following hypotheses:

H2. SC resilience is negatively influenced by disruptions impacts.
H3. SC robustness is negatively influenced by disruptions impacts.

2.6. The Impact of Supply Chain Disruptions

A SC disruption is described as an event that occurs in the chain and has the potential to negatively impact the performance of the SC as well as the normal flow of goods and materials within a SC (Behdani, 2013). The effects of the SC disruptions were reflected in a decrease in production rate, an increase in labor expenses, deteriorated service, customer dissatisfaction, a drop in revenue, a loss of brand reputation, and a drop in sales. This is typically the result of firms lacking measurements of disruption impacts on their SC network, as well as a lack of quantitative metrics (Wagner & Neshat, 2012). Moreover, several studies prove that the degree of complexity of SC's relationships could lead to various disadvantages. As a result of being exposed to a sudden disruption, whether due to natural disasters or strict restriction policies, production rates decreased, making it difficult to substitute suppliers.

Recently, SC suffered from several risk factors, some of which have piqued the interest of researchers due to their complexity and severity. However, various studies (Guha-Sapir et al., 2012) regard natural disasters as uncontrollable types of risk. Disruption impacts are expected to be due to natural and man-made disasters such as earthquakes, floods, hurricanes, terrorist attacks, and so on, which are expected to have a greater negative impact than operational risks (Tang, 2006b). The following Table

2.1 below shows the types of SC risk causes and their degree of impact (Anbumozhi et al., 2020).

Destruction events categorized via their source, severity, and length of the interval period (Dolgui et al., 2018). Those events have multiple impacts that strike several dimensions: individual, local, and global (Sawik, 2014). Natural disasters characterized by severe damaging effects on SC operations despite their low frequency of occurrence. Acute demand, immediate quick requests, a lack of supply, firm acquisition, coordinated distribution process, and sourcing limitations are examples of events with a high probability and reasonable influence (Scheibe & Blackhurst, 2018).

The influence of disruption could be rapid, but it could also take a while before the impact on SCP is obvious (Sheffi & Rice, 2005). Hence, a disruption in the SC might lead to a failure of the entire system and amplified impacts that could damage other participants (Wu et al., 2007). Generally, SC disruption, as opposed to risk, considers the probability and expected impact of an event. Thus, a "risk" is the probability and expected impact of a potential disruption.

Table 2.1: Causes of SC's risks.

Type of Risk	Risk	%	
Environmental	Natural disasters	59	Uncontrollable
	Extreme weather	30	Uncontrollable
	Pandemic	11	Influenceable
Geopolitical	Conflicts and war	46	Influenceable
	Export/Import restrictions	33	Controllable
	Terrorism	32	Influenceable
	Corruption	17	Influenceable
	Organized crime	15	Influenceable
	Maritime piracy	9	Influenceable
	Nuclear/biological weapons	6	Influenceable
Economic	Sudden demand shocks	44	Influenceable
	Volatility in commodity prices	30	Influenceable
	Border delays	26	Influenceable
	Currency fluctuation	26	Controllable
	Global energy shortage	19	Influenceable
	Investment restrictions	17	Controllable
	Shortage of labor	17	Influenceable
Technical	Information and communication disruptions	30	Controllable
	Transport infrastructure	6	Controllable

Figure 2.15 is taken from Sheffi and Rice (2005) and represents a disruption profile that displays the impact of disruption on an organization's performance over time. Based on the graph, it can be inferred that a shorter recovery preparation period can

speed up performance recovery. Thus, in conclusion, having a predefined plan can reduce the preparation time and minimize the impact of disruption, so it recovers faster.

In general, businesses frequently disregard the importance of SCRM (Ho et al., 2015). Literature has documented that more than 80% of businesses worldwide are concerned about the performance of SC (Marchese & Paramasivam, 2013), and it has been estimated that approximately 60% of those businesses lack a risk management system (Sáenz & Revilla, 2014). According to Staff (2019), the percentage of companies around the world that suffer from disruption in their SC every year is more than half. This could appear due to the circumstances that might be caused by individuals' actions or weather catastrophes. According to Ali et al. (2017), firms transition from a reactive SCRM system to proactive techniques to increase their resilience. SC represents the firm's resilience in the face of volatile and fluctuating circumstances and thus aids in mitigating the effects of unexpected events by forecasting risks and acting quickly.

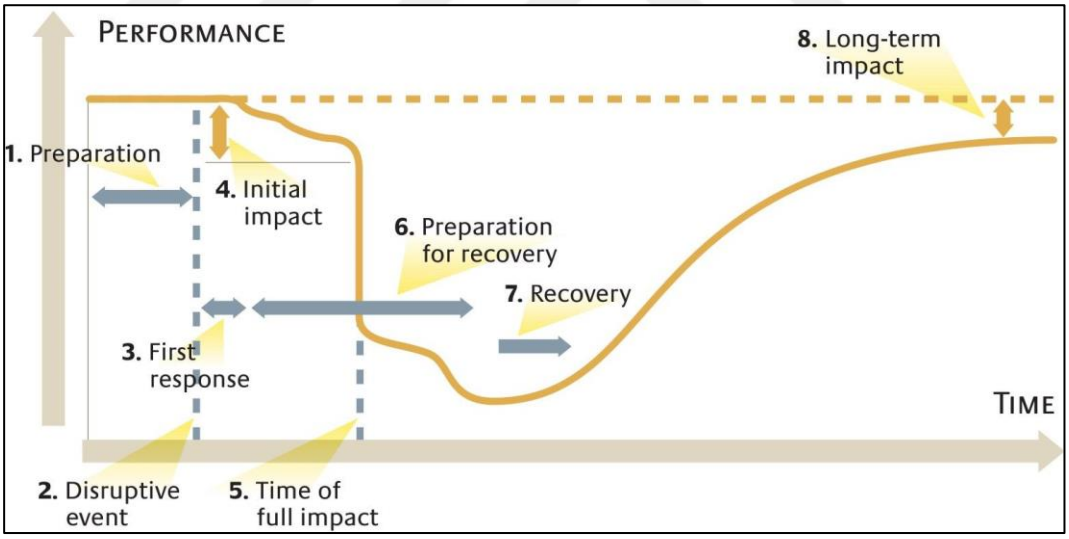

Figure 2.15: The disruption profile.

In the past years, several disruptions have affected firms and their supply chains. For example, in 2011, several natural disasters occurred and disrupted the SC all over the world, such as the tsunami in Japan and flooding in Thailand. As a result, it occurred in various industrial and exporter countries, causing significant damage to international companies' repute as well as their earnings and shareholder value; large corporations such as Toyota Motor, Apple, and Toshiba even experienced a decrease

in revenue, which is dependent on supply chain business continuity (Chongvilaivan, 2012).

Furthermore, Carvalho et al. (2021) explained the spread of economic shocks via SC because of the Japanese earthquake and Hurricane Sandy in the United States. Consequently, several companies that are remote from the disaster region are cooperating with their SC partners to decrease the negative impacts of disruptions (Iwao & Kato, 2019). Additionally, Barrot and Sauvagnat (2016) declared that the series of natural disasters that have occurred in the US have caused a shock in the economy, as represented by the decreased percentage of sales of companies indirectly via SC's disruptions in the disaster areas. Also, Todo et al. (2021) examined the economic shocks after Hurricane Sandy, with a result that shows companies that were located in the same disaster area and linked with suppliers in the same area have suffered from a decrease in their sales due to SC's disruptions. On the other hand, the opposite is true for international companies, which prove more resilient during pandemic disruptions due to their effective connections with the global market.

Furthermore, various civil wars around the world have created several changes in the strategies of the SC. In the period between 2018 and 2019, several firms were unable to absorb extra costs due to customs, which led to delays in the imports of metal products into the United States, leading to failure risks in the production line in the auto manufacturing plants (Banker, 2019). A worker strike at General Motors in 1996 was an example of a disastrous disruption impact. It finally resulted in a $900 million loss in quarterly earnings (Blackhurst et al., 2005).

Another example is the case of Ericsson and Philips. In 2000, a fire broke out at a Philips microchip fabrication facility, causing a shortage of chip supplies to the market and resulting in a massive loss for Ericsson of around $400 million in its sales for the cellphone (Sheffi & Rice, 2005).

Lee and Pierson (2011) clarified the reflected damage through entirely the global SC at all its stages, which obstructs its processes, according to Arto et al. (2015) the estimation of the impacts of the disaster on the global economy used to be approximated by the value of $ 139 x 10^9 in terms of impact on the workforce in 2016, approximately 28 x 10^3 workers were discharged due to shutdown of six manufacturers

of automobiles in Germany as a result of a contract dispute among Volkswagen and parts suppliers (Dolgui et al., 2018).

Di Stefano (2021) stated that the average activities of providing and requesting goods and services had shrunk as a result of the mandatory circumstances of the restrictive policies. The level of restrictions had reached its peak. On April 18, 2020, approximately one hundred and sixty countries shut down their work activities, and some of them shifted to doing remote work from home, according to the nature of their activities (Hale et al., 2020). Although the number of countries emphasizing closures had decreased by the end of 2020, their production processes were still facing a massively intensive effect. Thus, this affects the economy directly because of the SC's disruptions. Guan et al. (2020) found through their study that due to lockdown policies, there was a decrease of around forty percent in global production.

To conclude, to manage these risks, several firms are building supply chain resilience and robustness capabilities.

2.7. Pharmaceutical Supply Chain and COVID-19

The US Institute for Supply Management (ISM, 2020) declared that due to the COVID-19 epidemic, approximately 95% of organizations are experiencing different shapes of SC disturbances. The pharmaceutical industry globally is facing massive damage since China generates approximately 40% of the major ingredients of the drugs, thus locking out the production processes. Because most organizations are increasingly adopting an integrated complex SC (Chopoorian et al., 2020), disruptions would have significant amplified consequences (Ivanov et al., 2014 a, b). The global pharmaceutical industry was worth 1.27 trillion US dollars in 2020 (Mikulic, 2021). COVID-19 is causing a slowdown in pharmaceutical manufacturing due to material shortages and disruptions in the SC processes. The constraints imposed by the lockdown limit the supply and sale of goods. As a result, the Turkish pharmaceutical market has shrunk by 7% on a unit basis, falling to 2.2 billion units sold in 2020 (Şahin, 2021).

Because of the significant reliance on external raw materials, lockdowns and the temporary suspension of global trade wars cause delays in production and distribution around the world, with increasing demands on pharmaceutical products; for example,

the United States imports approximately 40% of generic pharmaceuticals from India (IBEF, 2020).

Several pharmaceutical industrial plants have been temporarily closed, causing a lack of raw materials as a consequence. Manufacturers are focusing more on lean manufacturing, outsourcing, and offshoring techniques as a result of cost pressures in SCs (Akbari, 2020). With a significantly reduced workforce, retailers struggled to process and get shipments out on time.

COVID-19 events, which are classified as high-impact, low-probability (HILP) events, pose a significant risk to SCs (Ivanov et al., 2019b). Epidemic outbreaks are treated as a distinct type of HILP SCR. Several firms have taken initiatives to improve the robustness and resilience of their global SCs, which have been affected by HILP events due to natural or industrial sources, such as hurricanes, earthquakes, tsunamis, and explosions. Consequently, several SCs have reported that the COVID virus has caused downstream disruptions and the closure of production and distribution activities. For example, Apple's assembler, Foxconn, is operating at a reduced capacity, as has been widely reported. Government lockdowns and a scarcity of parts supplies from Apple's own sub-suppliers have also harmed Apple's suppliers in Malaysia, South Korea, and Europe.

According to a recent Institute for Supply Management (ISM) survey of approximately 600 US firms, suppliers are operating at 50% capacity on average, resulting in longer final product lead times for 57% of those surveyed and revenue losses ranging from 5.6 percent to 15%. (Tempe, 2020). Because of shorter lead times and just in time (JIT), SCs have exacerbated the ripple effect of supply base disruption.

Because it is not limited to a specific geographic area or period, a pandemic has very specific implications for SCs. Various components of a SC, such as manufacturing, distribution centers (DCs), logistics, and markets, might become paralyzed within overlapping time frames as a result of this.

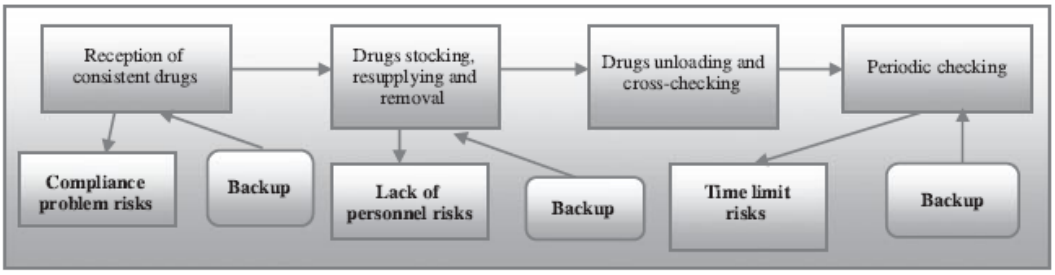

Figure 2.16: The pharmaceutical supply chain conceptual model.

As Figure 2.16 above shows, during the epidemics, several companies expected and recorded the reception of consistent drugs, which caused compliance problems, and in the case of drug stocking, resupplying, and removal, a lack of personnel risks appeared. While drug unloading and cross-checking necessitate periodic inspection, which has been factored into the time limit risks.

The effects of the epidemic, which started in March 2020 in Turkey, were immediately reflected in the monthly prescription numbers. The rapid decline in the number of prescriptions, which started in March, fell to the lowest level of the last 10 years in May, and fell to 20 million prescriptions. Despite some recovery in June, the total number of prescriptions decreased by 15% in 2020 compared to the previous year, returning to the pre-2016 period with 342 million prescriptions.

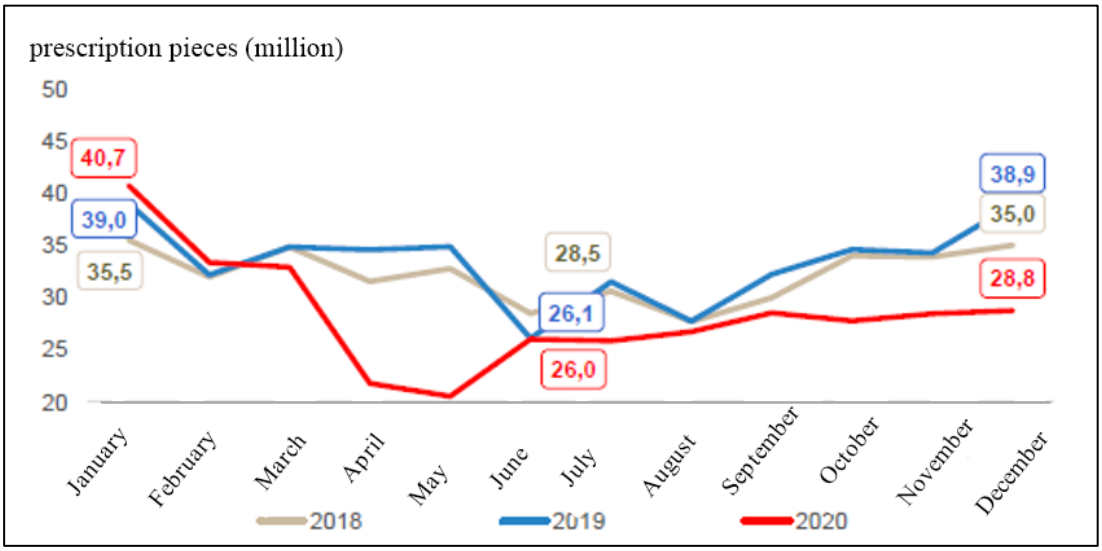

Figure 2.17: SGK number of monthly precisions.

Source: SGK Sağlik Istatistikleri, IEIS

As Figure 2.17 above shows, the number of prescriptions per piece has declined for the Turkish pharmaceutical companies in 2020 in comparison with the last two years, and it has recorded its minimum recording in the period between April and May of the same year.

In this thesis, the problems regarding the impact of SCRM's practices on performance during the COVID-19 pandemic of the Turkish pharmaceutical company SC is focused for study. Since Turkey involves suppliers from all over the world, the study will provide the possibility of its application on a global scale even as it investigates topics on a small scale. The study seeks to develop a scheme for assessing the factors that will affect SCs to ensure their safety from disruptions that may happen in the future. Regarding the field of study, it has been decided to conduct research on the pharmaceutical and industrial sectors in Turkey for several reasons. First, Turkey's economy is considered one of the fastest growing in Europe, with a global ranking of the 18th largest economy. Second, Turkey's associations are associated with universal SC exportation and importation throughout the world (European Union Trade, 2021). And the third reason Turkey is considered the 6th largest European economy (World Bank, 2019) is because the approach would help the SC risk managers decide to implement contingency plans and enhance the practices concerned with risk mitigation by testing whether SCRM influences both the robustness and the resilience of a supply chain.

2.8. Recent Studies

Wu et al. (2006) studied SCRM practices, including RI and RA, and disruption impacts for external and internal sources by applying their study to IT computer manufacturing in the US. They implemented an analytic hierarchy approach as their methodology. They discovered that firms should devote more resources to managing internal risks, and that HILP risks have a greater impact than controllable external risks.

Juttner and Maklan (2011) They studied the relationship between SCRES, SC vulnerability, and SCRM in the context of the recession caused by the financial crisis. The study was carried out on three different companies with global SCs: a cable supplier, a chemical products supplier, and a wood supplier. They implemented a

content analysis for their case study. In their study, they adopted the SCRM practices to be risk sharing, risk hedging through redundant resources, and SCR knowledge management. They found that SCRM practices had a positive impact on SCRES, and that SCRES had a positive impact on SCV throughout the financial crisis.

Wieland and Wallenburg (2012) studied the impacts of SCRM practices on SCP by studying the impacts of SCRM on agility and robustness. Also, how would agility and robustness affect SC's customer value and business performance, and how will SC's customer value affect business performance. They implemented their survey in three countries: Germany, Austria, and Switzerland, including the vehicle industry for both private and public companies of all sizes. They implemented SEM as an empirical methodology to analyse their survey data. They found that SCRM was critical to the company's agility and robustness. They also found that both agility and robustness can improve SCP. Agility positively impacts SC's customer value but has no direct impact on business performance. While robustness positively impacts both SCP dimensions directly, robustness is a requirement for dealing with risks from the supplier side, whereas agility is required for dealing with risks from the customer side.

Similarly, Charkhab et al. (2014) adopted the framework of Wieland and Wallenburg (2012) and discovered the same relationships, but they implemented their study in Iran and for the ceramic and tile industries. They implemented SEM using CFA as an empirical methodology to analyse their survey using Lisrel software. They found that SCRM positively impacts both agility and robustness. Also, agility and robustness positively impact SC's customer value and business performance as well. The SC's customer value positively affects the business's performance.

Simchi-Levi et al. (2018) combined flexibility and inventory strategies to enhance the SCROS through the implementation of a numerical case study of an automobile SC. Their method was accomplished by implementing optimization using a constraint generation algorithm. They found that providing two SCs did not mitigate SC disruption impacts. Also, making an optimal inventory decision depends on the flexibility of SC.

DuHadway et al. (2019) studied the effectiveness of SCRM practices by considering whether a disruption was caused by an intentional or inadvertent act and whether the source of the SC's disruption was internal or external. They developed

their propositions by integrating organizational information processing theory for managing uncertainty and revising prior literature on disruption management. They approved the importance of detecting risks for both intentional and inadvertent disruptions. while the effectiveness of SCRM practices varies in terms of risk mitigation and recovery.

Ganiyu et al. (2020) studied potential SCRs in Ghanaian firms and the impact of these SCRs and SCRMs' practices on firm performance. They used SEM to analyze the impact of SCRs and SCRM practices on the performance of Ghanaian enterprises. They found that SCRs negatively impact firms' performance, but SCRM practices positively impact firms' performance. They also discovered that prioritizing development and implementing SCRM practices improved operational efficiency and competitive advantages for businesses.

Ivanov and Das (2020) studied the impact of SC disruptions on SCRES, during COVID-19, simulating three scenarios for the epidemic's impact: an outbreak in China's manufacturing areas, an outbreak spreading to distribution centers in the United States, Germany, and Brazil, and an outbreak spreading to customers. They studied the measurement of the impact on SCRES by considering three aspects: 1. The speed of the epidemic propagation; 2. The resultant duration of the disruption at the distribution center nodes; and 3. The duration of the reduced (50% drop) demand period. They found that in China, SCs face negative impacts on their performance and suffer from stock-outs; besides, they experience price volatility. And they concluded that SCP depends on the epidemic's propagation velocity and duration, therefore, the distribution centers suffered from disruptions. They also concluded that optimal SCPs are recorded when recovery is implemented in SC.

Todo et al. (2021) studied how the SCROS maintain the links and how the SCRES substitute a disrupted partner with another. They accomplished their study on two levels: the SC's links level and the firm's level. In addition, they obtained their data from companies in Southeast Asian countries and India; the target companies are local and international. They adopted an empirical methodology and collected their data through a survey. They found that SCROS tends to maintain links by forming a group with similar agents, while SCRES is created by the geographic diversity of customers and suppliers. and all types of firms tend to be resilient and robust. SCROS

and SCRES led to higher performance. They also found that due to COVID-19 disruptions, firms tend to mitigate the DIs by substituting partners if their SCs are diversified across countries.

Drawing on existing literature on dimension selection and hypothesis development, dimensions were selected based on the frequency of measurements in the literature. Some of the chosen dimensions might highlight gaps in the previous studies. El-Baz and Ruel (2020) provided a comprehensive framework for SCRM, comprising the identification, assessment, mitigation, and control of SCRs. Table 2.2 shows the major studied dimensions of SCRM in literature, each of which experiences various risks; this compilation provides a detailed taxonomy of SCRM practices, SCRES, SCROS, and DIs following the framework, from which the questionnaire was constructed to represent the hypotheses.

As explained by El Baz and Ruel (2020) El Baz and Ruel (2020) studied the relationship between SCRM practices, DI, and SCRES and SCROS during COVID-19 by implementing variance-based PLS-SEM using SmartPLS (v. 3.2.6) and applying a survey on French firms for various business disciplines. They found a negative and significant direct relationship between DIs and RI and RA but no significant direct effect of DIs on SC risk mitigation and control. Also, they found that DIs and SCROS have a negative and significant direct relationship, but no significant direct effect of DIs was found on SCRES. Moreover, according to Al-Tamimi and Al-Mazrooei (2007) SCRM practices' indicators are risk identification, risk assessment and analysis, and risk monitoring.

Table 2.2: Frequency of SCRM dimensions used across the literature.

Dimensions		Sources	Frequencies	%
Disruption Impacts	*COVID-19*	El Baz and Ruel (2020), Ivanov and Das (2020), and Todo et al. (2021)	xxx	17%
	Natural Disasters	Shahbaz et al. (2019), and Parast (2020)	xx	11%
	Financial crisis	Juttner and Maklan (2011), Parast (2020), and Yu et al. (2019)	xxx	17%
	Intrernal Risks	Wu et al. (2006), DuHadway et al. (2019), Wieland and Wallenburg (2012), and Charkhab et al. (2014)	xxxx	23%
	Credit Risks	Al-Tamimi and Al-Mazrooei (2007)	x	5%
	External Risks	Wu et al. (2006), DuHadway et al. (2019), Wieland and Wallenburg (2012), and Charkhab et al. (2014)	xxxx	23%
	Supply Side Risks	Ganiyu et al. (2020), Shahbaz et al. (2019), and Parast (2020)	xxx	17%
	Demand Side Risks	Ivanov and Das (2020), Shahbaz et al. (2019), and Parast (2020)	xxx	17%
	Process Side Risks	Shahbaz et al. (2019), and Parast (2020)	xx	11%

	Logistic Side Risks	Shahbaz et al. (2019), and Wieland and Wallenburg (2012), and	xx	11%
	Inventory Risks	Ganiyu et al. (2020), Ivanov and Das (2020), and Hanafy and Shohaieb (2017)	xxx	17%
	Production Risks	Ganiyu et al. (2020), and Hanafy and Shohaieb (2017)	xx	11%
	Transport Risks	Ganiyu et al. (2020), and Ivanov and Das (2020)	xx	11%
Supply Chain Risk Management Practices	*Risk Identification*	Wu et al. (2006), Wieland and Wallenburg (2012), El Baz and Ruel (2020), Charkhab et al. (2014), DuHadway et al. (2019), Ganiyu et al. (2020), Al-Tamimi and Al-Mazrooei (2007), Hanafy and Shohaieb (2017)	xxxxxxxx	47%
	Risk Assesment	Wu et al. (2006), Wieland and Wallenburg (2012), El Baz and Ruel (2020), Charkhab et al. (2014), Al-Tamimi and Al-Mazrooei (2007) and Pettit et al. (2010)	xxxxxx	35%
	Risk Mitigation	Wieland and Wallenburg (2012), El Baz and Ruel (2020), Charkhab et al. (2014), and DuHadway et al. (2019)	xxxx	23%
	Risk Control	El Baz and Ruel (2020)	x	5%
	Risk Monitoring	Wieland and Wallenburg (2012), Charkhab et al.	xxx	17%

		(2014), and Al-Tamimi and Al-Mazrooei (2007)		
	Recovery	DuHadway et al. (2019)	x	5%
	Research and Development	Parast (2020)	x	5%
	Risk sharing	Juttner and Maklan (2011)	x	5%
	Risk Hedging through Redundant Resources	Juttner and Maklan (2011)	x	5%
	SCR Knowledge Management	Juttner and Maklan (2011)	x	5%
	Flexibility strategies	Simchi-Levi et al. (2018)	x	5%
	Inventory strategies	Simchi-Levi et al. (2018)	x	5%
Supply Chain Performance Measures	*Resilience*	Juttner and Maklan (2011), El Baz and Ruel (2020), Ivanov and Das (2020), Todo et al. (2021), Parast (2020), Yu et al. (2019), and Pettit et al. (2010)	xxxxxxx	41%
	Robustness	Wieland and Wallenburg (2012), El Baz and Ruel (2020), Charkhab et al. (2014), Simchi-Levi et al. (2018), Todo et al. (2021), Meepetchdee and Shah (2007), and Hanafy and Shohaieb (2017)	xxxxxxx	41%
	Agility	Wieland and Wallenburg (2012), and Charkhab et al. (2014)	xx	11%
	Supply chain's customer value	Wieland and Wallenburg (2012), and Ganiyu et al. (2020)	xx	11%

	Business performance	Wieland and Wallenburg (2012), Ganiyu et al. (2020), Hanafy and Shohaieb (2017), and Pettit et al. (2010)	xxxx	23%
	Financial performance	Wu et al. (2006)	x	5%
	Marketing performance	Wu et al. (2006)	x	5%
	Vulnerability	Juttner and Maklan (2011), and Pettit et al. (2010)	xx	11%

Disruption impacts can be demonstrated as environmental aspects, collaboration aspects, process aspects, supply aspects, demand aspects, and logistic aspects regarding the work of Shahbaz et al. (2019). Whereas Parast (2020) studied how the investment in R&D would mitigate the DIs and affect the SCP, he categorizes the DIs as supply, demand, environment, and process. His work viewed the SCP indicator as a test of its resilience. Similarly, Yu et al. (2019) investigated the impact of dynamic SC on SC disruptions orientation and SCP and defined SCRES as SCP indicators by testing it from a financial standpoint. Pettit et al. (2010) also studied the impact of disruptions on SCRES.

Wieland and Wallenburg (2012), similar to El-Baz and Ruel (2020), chose their SCRM practices to be identification, assessment, mitigation, and control. However, in their work, they considered robustness and agility as SCP indicators. Similarly, Hanafy and Shohaieb (2017) and Meepetchdee and Shah (2007) studied robustness as a SCP measure.

After choosing these dimensions, 14 hypotheses have been developed for the purpose of the research, as extracted from previous literature. In addition to using the El-Baz and Ruel (2020) framework, the study was thought to be useful in another country studying various disciplines using the same methodology.

3. METHODOLOGY

The methodology of the study is followed by the steps displayed in Figure 3.1.

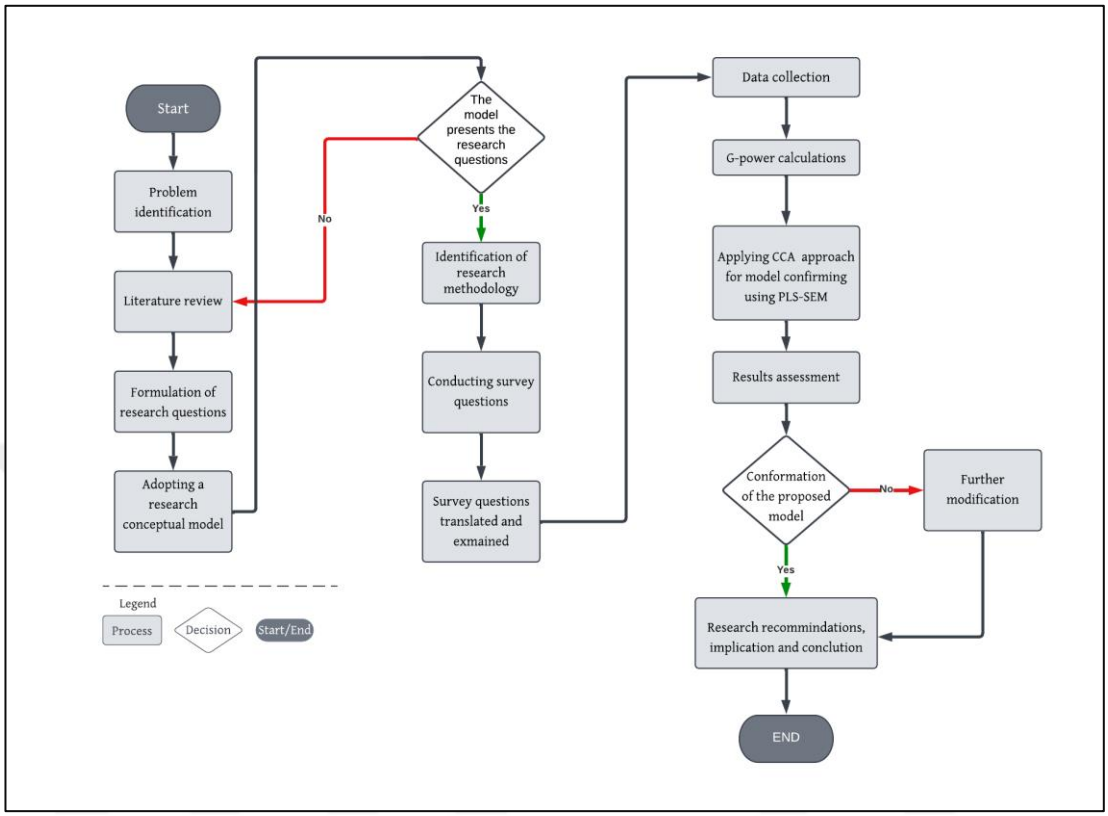

Figure 3.1: Methodology flowchart**.**

The collection of data is done by the developed questionnaire. The questions are extracted from previous studies in the literature and examined by the expert analysis to ensure that all the measurement items are clear and to avoid ambiguity the items were reduced from table B.1 to the items in table B.2 respectively (Appendix B). Then it is translated into the Turkish language, and the final improvement is integrated as shown in table B.3(Appendix B).

A photo copy of the questionnaire is shown in the end of (Appendix B) and is divided into two parts with total of 36 questions;

The first part consists of 5 questions cover general information which are: Respondent Titles, Number of Employees, Experience/Age of Company, Work Experience in the Industry, and Work Experience in the Current Company.

The second part covers seven aspects, Disruption impacts, Risk Identification, Risk Assessment, Risk Mitigation, Risk control, Resilience, and Robustness. This part

includes 31 closed-end questions based on ordinal scale, where 12 questions correspond to Disruption impacts, 5 questions correspond to Risk Identification, 3 questions correspond to Risk Assessment, 2 questions correspond to Risk Mitigation, 3 questions correspond to Risk control, 4 questions correspond to Resilience, and 2 questions correspond to Robustness.

Respondents were asked to indicate their degree of agreement and extent with each of the questions on seven Likert scale. the items and their references are shown in table B.2 (Appendix B). The variables with their scale type found in table A.1 (Appendix A)

The CCA approach is considered a systematic set of steps executed for confirming measurement models when using PLS-SEM. This approach is preferred to investigate the research questions because CCA is suitable for both exploratory and confirmatory analysis (Hair et al., 2020). In addition, CCA analyzes independent and dependent variables together. Moreover, it improves the construct validity and the coverage of the content since the number of retained items that measure a construct with this method is higher than in other approaches, and it offers the determination of construct scores (Rigdon et al., 2019).

Structural equation modelling (SEM) is a statistical confirmatory approach applied to assess the relations among multiple observed and latent variables, and it consists of two basic components: a structural model and a measurement model. It increases the ability to make effective evaluation measurement models and structural paths, especially for this proposed structural model, which involves multiple dependent variables, latent constructs based on multi-item indicator variables, and multiple levels of constructs (Astrachan et al., 2014). This approach allows the measurement error to be observed and thus minimized. Several computer programs, such as SmartPLS, are used to apply the SEM approach.

Latent variables, also known as exogenous (independent variables), cannot be observed but could be detected by measuring their effects on the observed variables (dependent variables), which are known as endogenous variables and are considered

measurable. Figure 3.2 below describes the difference between latent and observed variables, which are connected reflectively.

For the model estimation in this multivariate data analysis, Partial least squares: PLS-SEM using SmartPLS V. 4.0.8 has been employed. PLS-SEM is an advanced and appropriate measurement model, considered to be a specific type of VB-SEM developed by Herman Wold (1982). It analyzes the total variance and examines both a measurement model and a structural model, and it has been chosen for various reasons extracted from the literature. One of its criteria is that its exploratory characteristics help to explore the relationship among latent and observed variables, so thus it suits the current study since the model is still under development (Hair et al., 2011, P.144), and it is an extension of an existing structural theory (Baz et al., 2020). In addition, PLS-SEM does not assume certain data distributions (Jannoo et al., 2014).

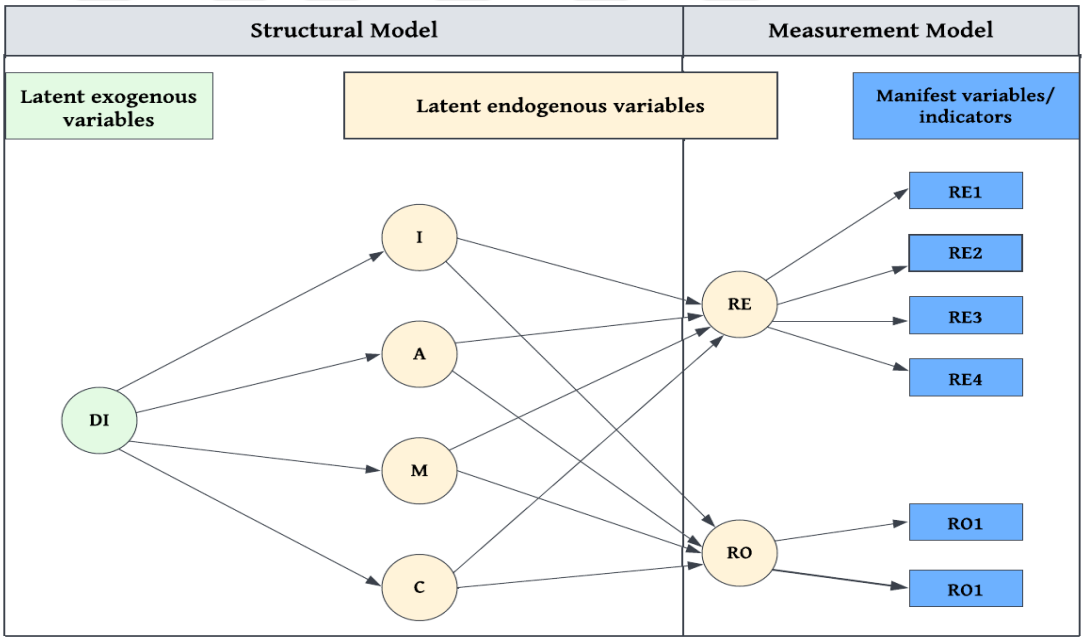

Figure 3.2: Endogenous and Exogenous variables.

Moreover, PLS-SEM can converge with a small sample size (Goodhue et al., 2012). Besides that, it is effective in dealing with complex models (Akter et al., 2017), which suits this case study, its predictively explanatory nature of the relationships is due to the optimization of the residual variance (Hair et al., 2011, P.144).

The conducted model is assumed to be a reflective measurement model. The endogenous are affected by the exogenous variables so that any changes made to the constructs will be sequentially reflected on the items. Thus, the endogenous are

assumed to be related and have the same meaning because of the common cause (Said et al., 2020). Due to this type of relationship, this measurement is a reflective model (Sarstedt et al., 2016).

Evaluation of the reflective model using PLS-SEM is usually done by following a systematic process that ends by assessing the outer model and the inner model. For the outer model, or could be referred to as the measurement model, the analysis is carried out to assess the relationships between the items and the corresponding construct, while for the inner model (structural model), the relationships between the constructs are presented. Figure 3.3 below represents the inner and outer models (Wong, 2014).

Following the recommendations of Hair et al. (2020), the CCA with reflective measurement for this model was carried out in two steps: The first step is to examine the measurement model, and the second step is to evaluate the structural model by testing the estimated hypothesis and observing the relationship indicators between exogenous and endogenous variables specified in the path diagram.

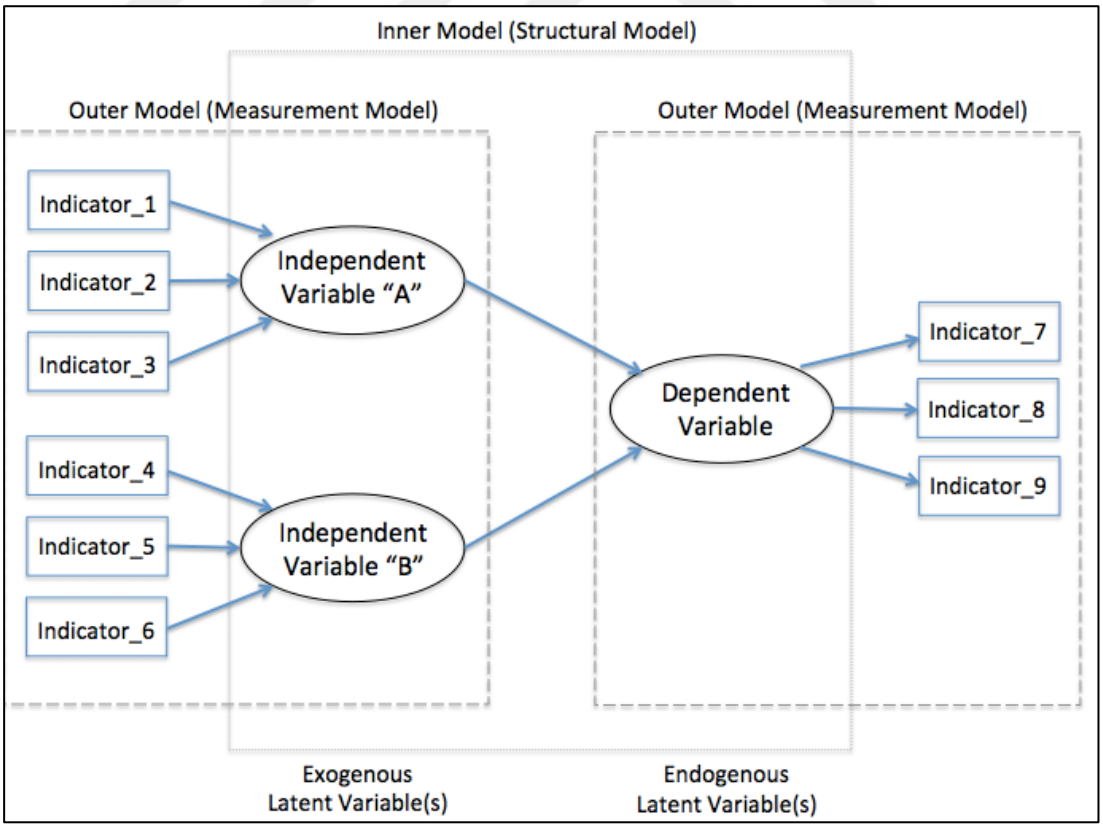

Figure 3.3: Inner vs Outer model in a SEM diagram**.**

3.1. Measurement Model Assessment

The general procedure for describing the measurement model assessment is explained by the following five steps: Thus, the fundamental purpose of this stage is to evaluate the assumptions related to the reliability and validity of the structural measurement model.

Step 1 is accomplished through the assessment of the indicator loadings and their significance. Using SmartPLS V. 4.0.8 software, the establishment of the first step is done by running the PLS algorithm and choosing the outer loading results, and to make the estimation more confirmatory, 10,000 iterations have been set to maximize the value of the determination coefficient (R^2) as recommended by Hair et al. (2020). As a rule of thumb, item loading values should be significant and have a value of 0.708 (Hair, Ringle, & Sarstedt, 2011). To have a 0.708 loading explains that half of the variance in the items is explained by their latent constructs (Sarstedt et al., 2016). Thus, the larger the loading value, the more reliable the measurement model (Sarstedt et al., 2016). Another rule of thumb is that if the results of the indicators' loading vary between 0.4 and 0.7, the omitting process is recommended if it improves composite reliability; otherwise, it is not (Hair et al., 2014). Figure 3.4 below explains the outer loading relevance testing by using CCA for testing the reflective measurement model as suggested by Hair et al. (2017).

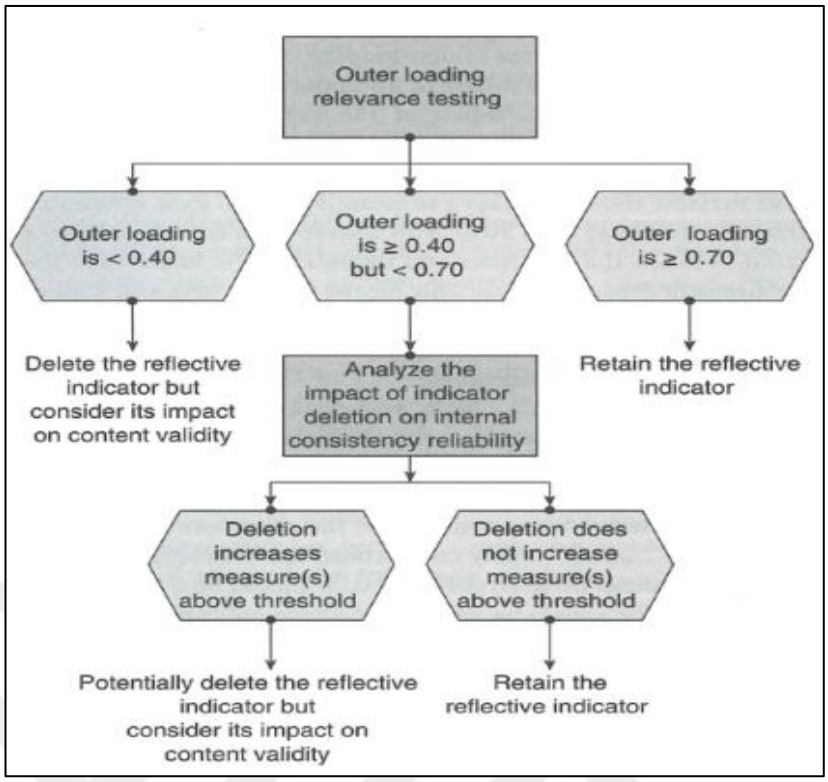

Figure 3.4: Outer loading relevance testing.

In the second step as described in the first one, the reliability of the items measures the amount of variance among each item and the associated indicator (Hair, Black, et al., 2019), and this is accomplished by squaring the outcomes of each single indicator loading.

In step 3 the reliability of the construct is assessed, composite reliability (CR) is considered to be more accurate and preferred to test the convergent validity, thus it is recommended to be assessed and reported (Hair et al., 2019), CR values varies from 0 to 1 and it is recommended to be above 0.7, very high composite reliability > 0.95 may indicate that multiple indicators are measuring the same concept, and this is called redundancy. The Composite reliability could be written as

$$\rho_C = \frac{(\sum_i l_i)^2}{(\sum_i l_i)^2 + \sum_i var(e_i)} \qquad (1)$$

In this equation, *li:* is the outer loading. For, *i*= 1, 2, 3….. n where *i* represent natural numbers. Var (e_i) is the population variance where Var (e_i) = 1-l_i^2 = σ^2 .

The convergent validity analysis is accomplished by the fourth step. Where the Average Variance Extracted (AVE) is measured. This metric reflects the amount of the variance that constructs explains in its individual item variable relative to the overall variances of items in the reflective model. AVE should be ≥ 0.50 (Chin, 1998). The AVE for the constructs ξ_j is:

$$\text{AVE}_{\xi j} = \left[\frac{\sum_{k=1}^{k_j} \lambda_{jk}^2}{\sum_{k=1}^{k_j} \lambda_{jk}^2 + \theta_{jk}}\right] \qquad (2)$$

Equation 2 above represents the mathematical equation that describes the Average Variance Extracted metric, where λ_{jk} is the indicator loading, Θ_{jk} the error of the variance of the k^{th} indicator (K= 1,…. K_j) of construct ξ_j, K_j represents the number of indicators of ξ_j. This mathematical model shows the percentage of variation in the measures is in the construct. In the case that all of the indicators have mean of zero, and variance of 1 which are called standardized indicators, the equation will be simplified to:

$$\text{AVE}_{\xi j} = \left[\frac{1}{\text{Kj}}\right] \sum_{k=1}^{k_j} \lambda_{jk}^2 \qquad (3)$$

where the AVE will be equal to the average squared standardized loadings.

Discriminant validity assessment is used for analysing the relationship between latent variables. to check the discriminant validity of PLS model, two approaches have been followed: First, it is detected by the Heterotrait-Monotrait (HTMT) ratio as new approach to assess discriminant validity in VB-SEM (Henseler et al., 2015). Which is defind as an estimate of the correlation between two constructs ξ_1, ξ_2. Where, Monotrait terms provide values of the correlations among items within the same construct, and the Heterotrait terms represents the correlations among items from the two separate indicator groups. From the advantages of HTMT that it does not require a factor analysis to obtain factor loadings, nor does it require the calculation of construct scores. This allows for determining the HTMT even if the raw data is not available, but the correlation matrix is (Schmitt, 1978). The equation below shows the detailed written equation that at present the Heterotrait-Monotrait (HTMT) ratio.

$$HTMT_{ij} = \underbrace{\frac{1}{K_i K_j}\sum_{g=1}^{K_i}\sum_{h=1}^{K_j} r_{ig,jh}}_{\text{average heterotrait–heteromethod}} \div \underbrace{\left(\frac{2}{K_i\,(K_i-1)}\cdot\sum_{g=1}^{K_i-1}\sum_{h=g+1}^{K_i} r_{ig,jh}\cdot\frac{2}{K_j(K_j-1)}\cdot\sum_{g=1}^{K_j-1}\sum_{h=g+1}^{K_j} r_{jg.jh}\right)^{\frac{1}{2}}}_{\text{geometric mean of the average monotrait–heteromethod correlation of construct } \xi_i \text{ and the average monotrait–heteromethod correlation of construct } \xi_j}.$$

For more simplified formula:

$$HTMT_{ij} = \frac{A}{\sqrt{B.C}} \qquad (5)$$

where:

A: is the mean of all pairwise correlations between items of first construct and the items of the second construct, which present in the above detailed equation the first part, the average Heterotrait-heteromethod correlations.

B: is the meaning of all pairwise correlations between items of first construct, which present the first term part under the square root as the average monotrait-heteromethod correlations.

C: is the mean of all pairwise correlations between items of second construct, which present the second term part under the square root as the average monotrait-heteromethod correlations. The matrix in the Figure 3.5 below represents an example of HTMT values of correlation coefficients within items for a model with two constructs ξ_1, ξ_2 respectively. And for each construct 3 items have been presented X_1, X_2, X_3 measured the construct ξ_1 and, X_4, X_5, X_6 for ξ_2.

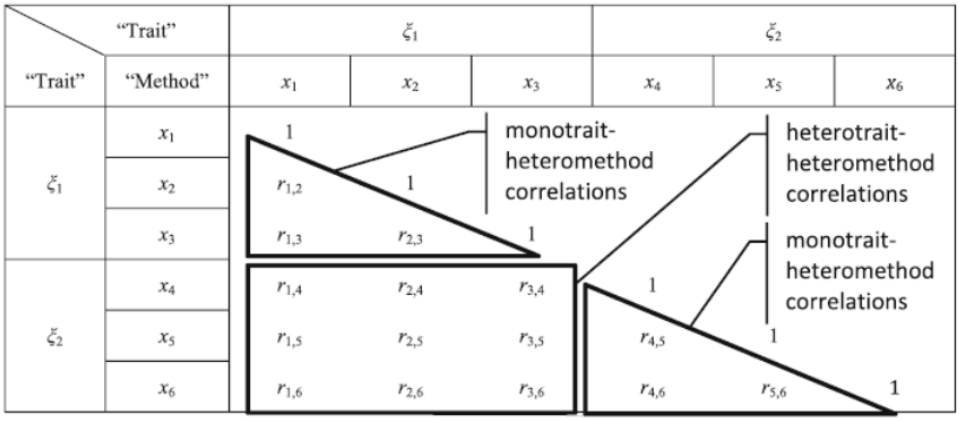

Figure 3.5: HTMT matrix.

Table 3.1: Recommended values for HTMT

Reference	**Recommended value**
Henseler et al. (2015)	Less than 0.9
Kline (2011)	Less than 0.85

As shown in Table3.1 above the recommended values that should be accepted according to literature. High values of HTMT indicates a problem in discriminant validity, if (HTMT) > 0.90, then the constructs are not distinct (Henseler et al., 2015). If the (HTMT) values are larger than 0.90 and close to 1 then, Secondly approach is considered as procedure to improve the discriminant validity values, and that is done by the check of the cross loadings which should give for each block of indicators a higher loading for each latent variable measured than the indicator for the other latent variable, if the case is not then the indicator with lower loading should be detected to increase the HTMT ratio. Another method is followed to improve the discriminant validity is by the removal of items having the lowest correlation with other items of the same construct, and by the removal of items having the highest correlation with other items of other construct. As shown in Figure 3.6 below steps for discriminant validity assessment using HTMT (Hair et al., 2017).

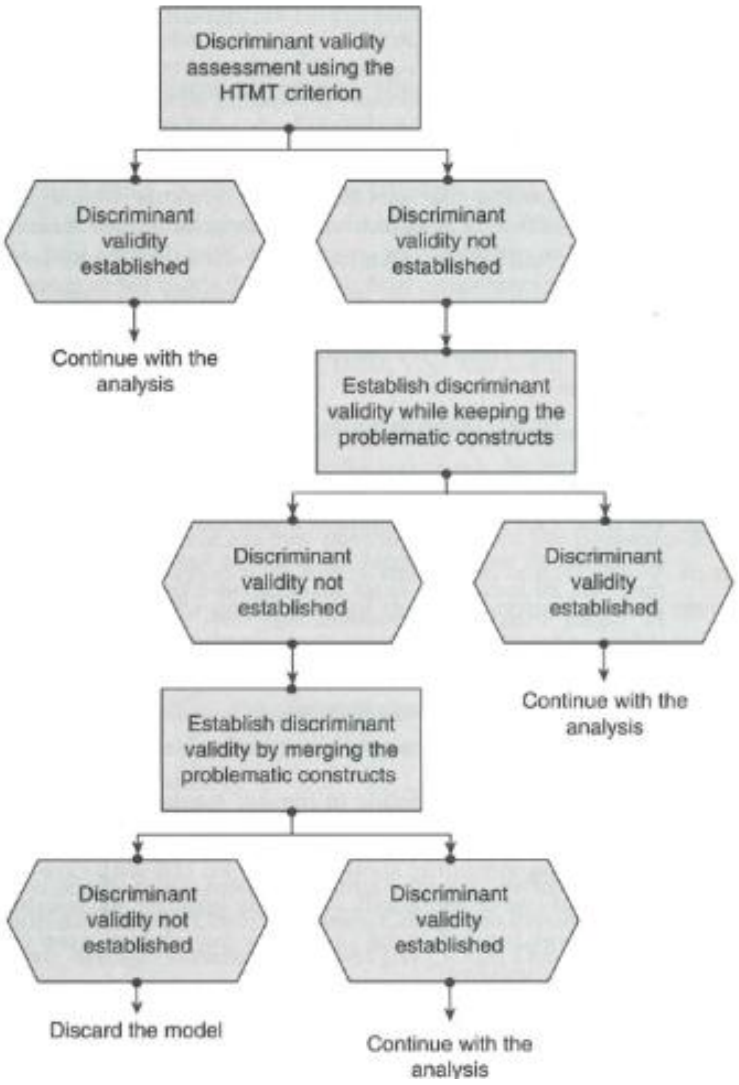

Figure 3.6: Handling discriminant validity problems.

3.2. Evaluation of the Structural Model

With the developed PLS-SEM using CCA method, a recommended steps by (Hair et al., 2020) is followed in assessing the structural model. According to Hair et al. (2020) before the assessment procedure a confirmation of the structural model by CCA should be insured and confirmed. For the purpose of the study a one-tailed test has been applied for the analysis of this model, because the coefficients are assumed to have signs in order to reflect the hypothesis (Kock, 2015).

Following 6 steps the assessment start with the evaluation of the structural model collinearity statistics by the examination of the variance inflation factor (VIF), which

measures the multicollinearity between variables as described with the following equation.

$$\text{VIF} = \frac{1}{TOL} \qquad (6)$$

$$\text{TOLerance} = 1 - R_{x_i}^2 \qquad (7)$$

Where: $R_{x_i}^2$ is the correlation between one indicator and the other indicators in the same construct.

The greater the VIF value and the more multicollinearity with the specific independent variable, the closer the R^2 value is to 1. VIF < 3.0 is considered as a good indicator (Hair et al., 2020). Multicollinearity problem causes changes in the size and the signs of the beta (β) coefficients. The recommended solution for multicollinearity problem is by combining the separate construct into conceptually similar and theoretically lower order construct (Cenfetelli & Bassellier, 2009).

The second step is to examine the size and the path coefficients in order to test the hypothesized relationships between constructs. Path coefficients value varies from +1 to -1; if the value is close to zero then it is considered to indicate weak relationship between the constructs. On the other hand, values closer to 1 have stronger relationship.

Step 3 provide a metric used in the assessment of the structural model prediction, which called the coefficient of determination ($\boldsymbol{R^2}$). Which explains the degree of relationship between independent variables and the dependent variables constructs. Cohen (1988) suggested that as a rule of thumb $\boldsymbol{R^2}$ values for endogenous latent variables is 0.26 is substantial, 0.13 moderate, and 0.02 as weak. Some researchers examine the adjusted $\boldsymbol{R^2}$, which considered to be useful when there are several nonsignificant predictor constructs in the structural model (Hair, Hult, et al., 2017).

Assess the level of R^2 :

$$R_{adj}^2 = 1 - (1 - R^2)\frac{n-1}{n-k-1} \qquad (8)$$

Step 4 tests the effect sizef^2, which is the change in R^2, when exogenous variable is removed from the model, and it is considered as predictive metric. $f^2 \geq 0.02$ is small, ≥ 0.15 is medium, and ≥ 0.35 is large (Cohen, 1988).

$$f^2 = \frac{R^2_{Included} - R^2_{Excluded}}{1 - R^2_{Included}} \qquad (9)$$

As it has been mentioned two previous metrics were considered to be predictive which are R^2,f^2, and the third one is in this 5^{th}step which is called blindfolding Q^2which measures whether the model has predictive measure relevance or not.

$$q^2 = \frac{Q^2_{Included} - Q^2_{Excluded}}{1 - Q^2_{Included}} \qquad (10)$$

Step 6 the PLSpredict which splits the total sample into subgroups of equal size, where k presents the number of subgroups. The (k – 1) subgroups will be then selected and combined to a single analysis sample, the other subgroups then would be predicted until all of the k originals subgroups are predicted the process is considered to be completed.

It is recommended to have the sample size of the subgroup to be N = 30 (Hair et al., 2019). The amount of prediction errors is quantified by PLSpredict. However, the focus should be on the theoretical primary endogenous construct not on the prediction errors. A verification of the predictions outperforms by examining the naïve benchmark (Shmueli et al., 2019), if the value resulted above zero the other prediction statistics could be performed. The model considered to be lack of predictive power if the resulted root mean squared error (RMSE) has higher values compared to naïve and vice versa. Also, if the majority indicators of dependent construct have higher prediction errors in comparison with the naïve linear regression mode (LM) benchmark then the model is classified to have low predictive power. Whereas if an equal portion or the minority of the dependent construct indicators have higher prediction errors compared to the naïve LM benchmark, then the model has medium predictive power.

In the last step further, advanced analysis is considered for the application of PLS-SEM, such as the application of some categories mediation and moderation to check and evaluate the PLS-SEM analysis.

4. IMPLEMENTATION AND RESULTS

4.1. Data Collection

The contact information about the pharmaceutical companies was collected and administered for the survey via LinkedIn to a targeted sample such as suppliers, executives, and risk managers with a letter of intent showing the objective of the study.

The population of the sample study was specified to be accessible population by targeting the pharmaceutical supply chain in Istanbul, Turkey, to reflect the required sample size as a case study. The population of the targeted sample was extracted from an official statistical site (Istanbul Ilaç Firmaları, n.d.). The total population was found to be made up of 226 Istanbul pharmaceutical companies registered in the Turkish pharmaceutical directory system and a total of 14,189 drug records belonging to these companies (Istanbul Ilaç Firmaları, n.d.). During the COVID-19 crisis, a questionnaire using Google Form was established to reach respondents online. Respondents were mostly contacted via email and the LinkedIn website, and 102 respondents contributed to the study.

4.1.1. Sample Size Calculations

The G*power V.3.1.9.7. analysis tool was used to estimate an adequate sample size (Faul et al., 2009). After establishing the study objectives and hypotheses, the F-statistical test was chosen following the recommendations of El Baz et al. (2020) using the test series drop-down menu. A simple linear regression technique was used to understand the association between the predictor variables and the dependent variables, as shown in Figure 4.1.

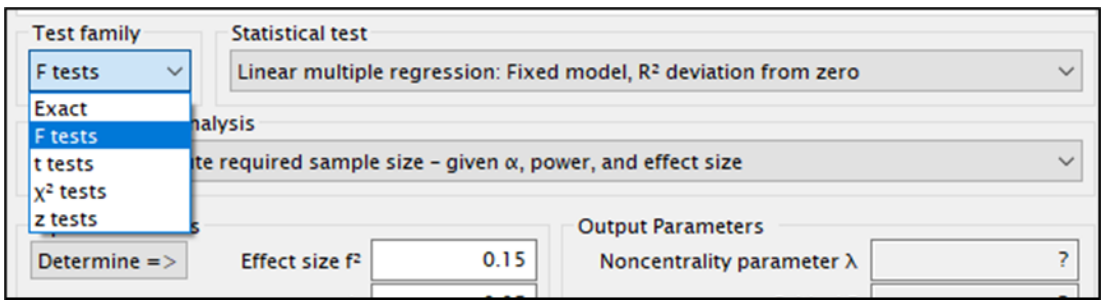

Figure 4.1: Statistical tests in G*power software.

In step 2, considering the sample size to be calculated and according to the available variables, a priori analysis was performed as "the type of power analysis" to perform the sample size (N) calculations before conducting the study. as shown in Figure 4.2.

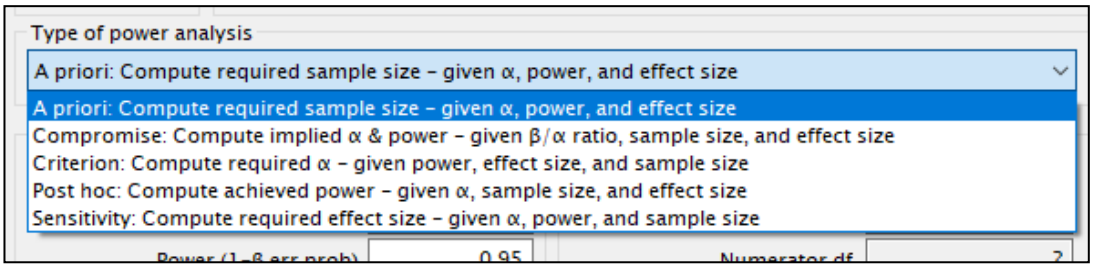

Figure 4.2: Types of power analysis in G*power software.

The predetermination of the sample size needs four major factors to be taken into consideration. Thus, the sample size N is computed as a function of statistical power (1-β), where β is the probability of accepting wrong null hypotheses (II error), the significance level alpha is the probability of rejecting the null hypothesis when they are true type I errors, and the effect size helps to determine the population effect size that is appropriate for the study. Finally, the number of predictor variables in the regression model Figure 4.3 below describes the four parameters that determine the sample size.

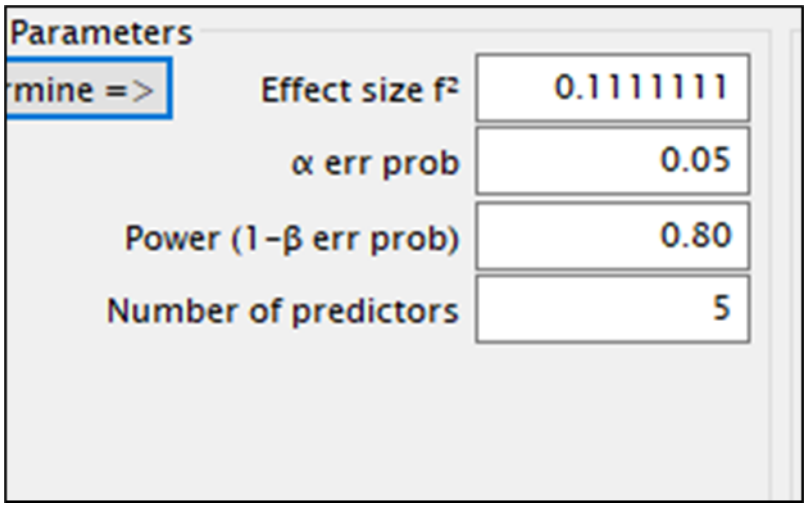

Figure 4.3: Parameters to determine the sample size.

Following the recommendations of Cohen (1988), the analyses were based on minimum values. The statistical level of significance Alpha 5%, which is the probability of the rejection of the null hypothesis when it is true, thus committing Type I error. The next factor to be determined is the population effect size f^2 which is

function of R^2, based on prior research, a minimum R^2 value of 0.10, R^2 is the projected effect size, which will determine the population effect size appropriate for the study (El Baz & Ruel, 2020). Where for multiple regression analysis:

$$f^2 = R^2_{Y.B}/1\text{-}R^2_{Y.B}$$

The value was found to be 0.111, which is considered a medium effect size. According to Cohen (1992) proposed that a medium effect size is desirable as it would be able to approximate the average size of observed effects in various fields.

Next to determine is the statistical power, which is expressed as 1-β, where β represents the probability of accepting the wrong null hypothesis and committing Type II error, and according to Cohen (1992) suggestions, the power is fixed at 80%. The fourth and last factor to determine is the number of predictors in this regression model, which is five predictors for the supply chain performance (SCP) construct. using the F-test for a linear multiple regression: fixed model, R^2 deviation from zero. The priori test for computation of the required sample size indicated that required representative sample size is122.

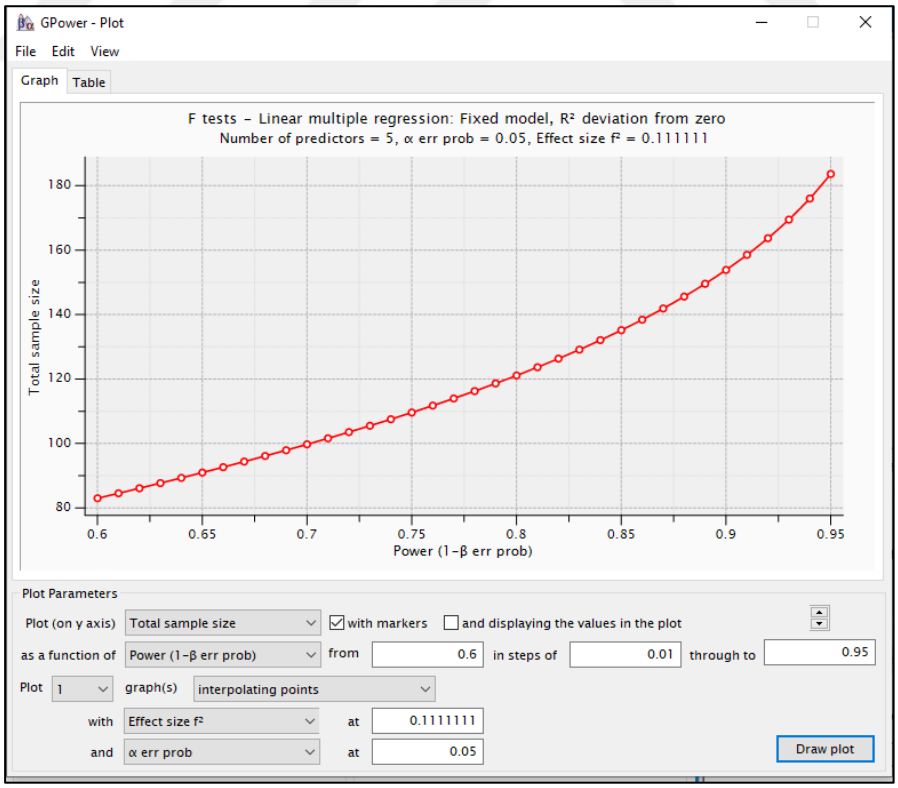

Figure 4.4: The total sample size required at each power level.

Figure 4.4 shows a graph presents the relationship between the total sample size required with a variation of the power levels for fixed number of predictors = 5, effect size of 0.111 and α of 0.05.

In contrast, a post-hoc analysis is typically conducted after the completion of the study. As the sample size N is given, the power level (1-β) is calculated using the given N, the effect size, and the desired α level. Therefore, a post-hoc G*Power analysis was done for the same conditions, a minimum R^2 of 0.10, a sample size of 102, and five predictors revealed that the statistical power achieved through the study's sample size was 0.71, which is below Cohen's (1988) recommendations. However, the number of obtained responses was approximately close to the required sample size but below expectations which was so difficult to achieve because of the companies' policies since only 102 contributions have been received in a four-month period [from 04/04/2022 to 24/08/2022]. The Standard Deviation (STD) for all indicators of the whole sample size have been calculated as displayed in table A.2 (Appendix A) to eliminate non-variate responses which are invalid. And since there was no non variate observations have been found the number of responses kept as 102.

4.2. Analysis of Descriptive Statistics

4.2.1. Respondent Titles

The sample of supply chain (SC) partners' respondents consisted of 47 (46.1%) supply chain managers, 30 (29.4%) purchasing managers, 9 (8.8%) both for export sales managers and logistics managers, and 7 (6.9%) warehouse managers (N = 102) as Table 4.1 below illustrates.

Table 4.1: Frequency distribution for respondents' titles.

Respondent titles	Frequency	Percent
Warehouse Manager	7	6.9
Export Sales Manager	9	8.8
Logistics Manager	9	8.8
Purchasing Manager	30	29.4
Supply Chain Manager	47	46.1

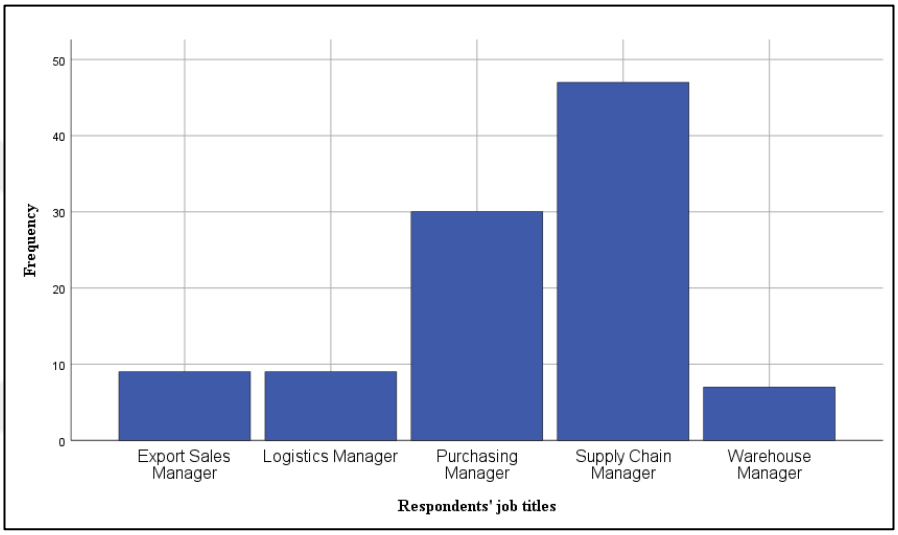

Figure 4.5: Respondents' job titles vs frequency.

Figure 4.5 above shows the job titles of the respondents. Supply chain mangers and purchasing managers represents the majority of the sample size. Others includes export sales managers, logistics managers, and warehouse managers.

4.2.1. Number of Employees

Figure 4.6 shows the number of employees that are working in the respondents' companies. More than half of the respondents (52%) work within large business organizations. And with a total of approximately (28%) of the respondents work within medium-sized enterprises. While a small minority work within micro and small enterprises.

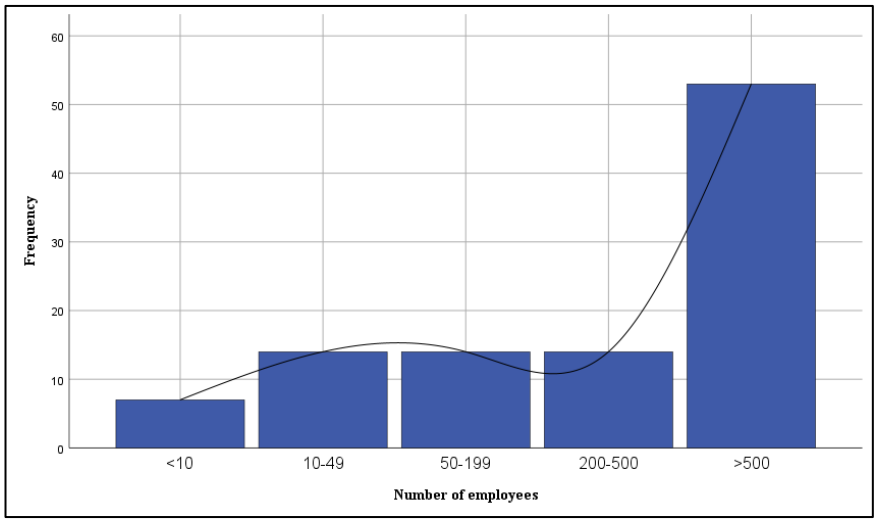

Figure 4.6: Number of employees for respondents' companies

4.2.2. Experience/Age of Company

This chart 4.7 illustrates the experience/age of respondents' companies in years. Thus, 36 (35.3%) of respondents work for companies >50 years of age. And 13 (12.7%) work in companies that are 30–50 years old. While 12 (11.8%) work within companies that have an average age of 20–29 years, 18 (17.6%) work in companies that have 10–19 years of experience. And 23 (22.5%) work at companies that have been established for less than 10 years.

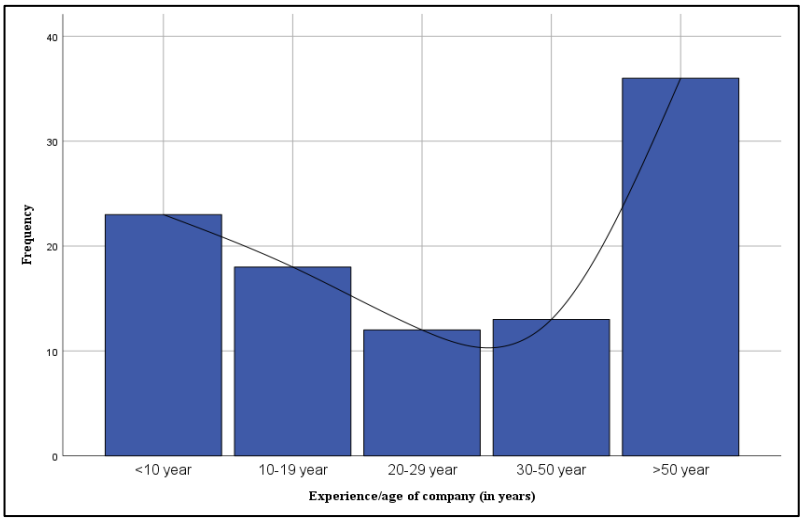

Figure 4.7: The frequency of company age (in years) for respondents.

4.2.3. Work Experience in the Industry

The majority of the respondents have an experience in the industry of 11 years or more. And the minority have 5 years or less. While a tiny minority have an experience about 6-10 years as Figure 4.8 represents.

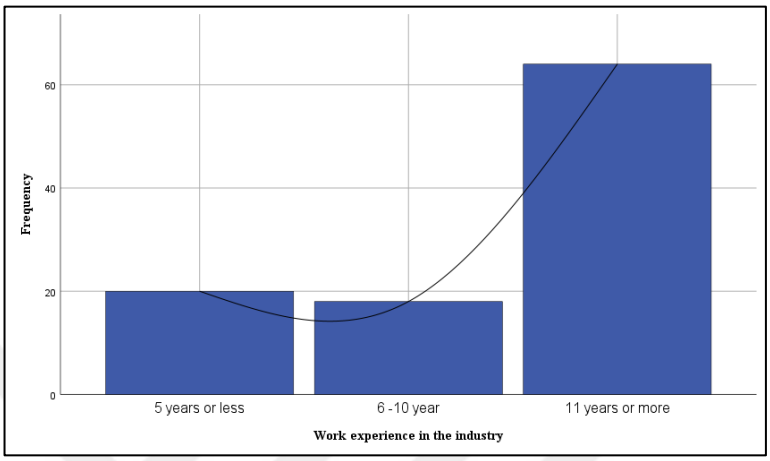

Figure 4.8: The frequency of work experience for the respondents in the industry.

4.2.4. Work Experience in the Current Company

Figure 4.9 shows that the large majority of respondents have worked at their current companies for 5 years or less. while a tiny percentage have experience of at least 11 years and between 6 and 10 years.

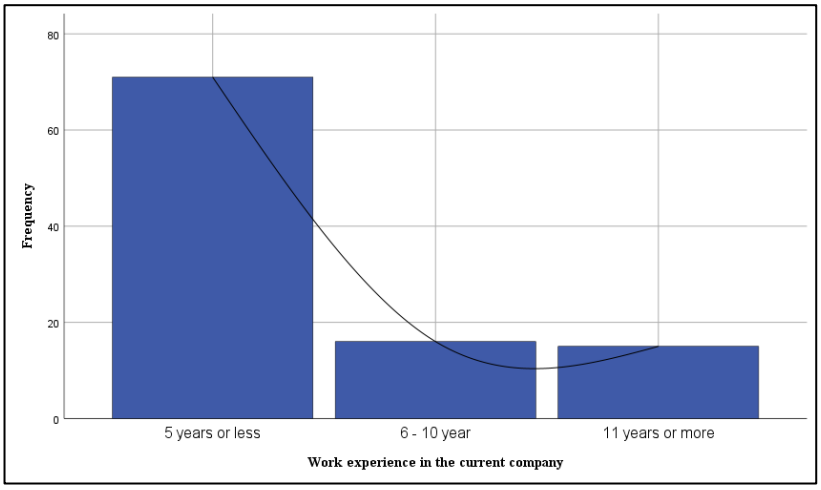

Figure 4.9: The frequency of work experience for the respondents in their current companies

The data was collected from the SC pharmaceutical companies from five disciplines that include supply chain manager (n = 47), purchasing manager (n = 30), logistics manager (n = 9), export sales manager (n = 9), and warehouse manager (n = 7). The descriptive statistics in table 4.2 below show that the majority of each discipline work

in their current company with an experience of less than 5 years, figure 4.10 summarizes the result in graphical scheme.

Table 4.2: Work experience in the current company across respondent titles.

		Work experience in the current company			Total
		5 years or less	6 - 10 year	11 years or more	
Respondent titles	Export Sales Manager	8	1	0	9
	Logistics Manager	4	2	3	9
	Purchasing Manager	22	6	2	30
	Supply Chain Manager	31	7	9	47
	Warehouse Manager	6	0	1	7
	Total	71	16	15	102

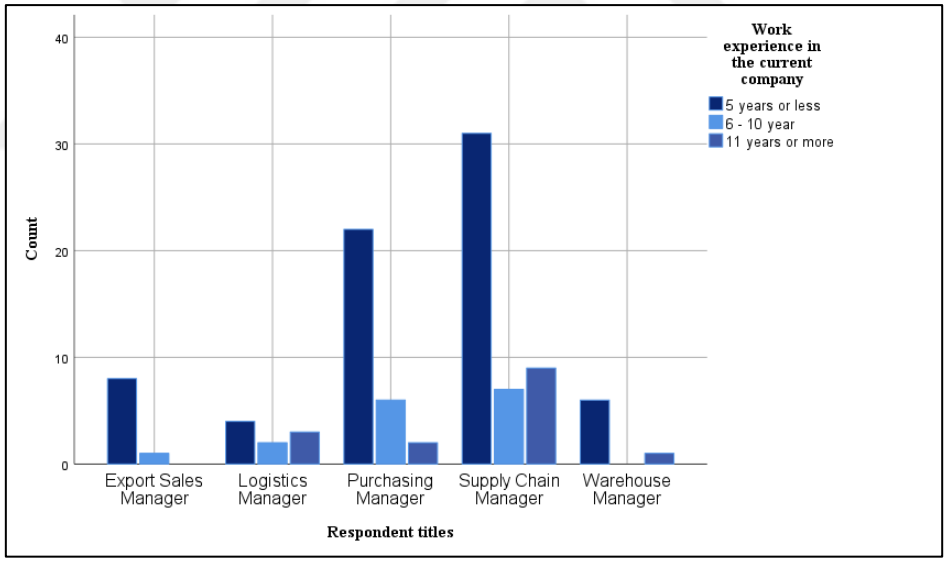

Figure 4.10: Work experience in the current company across respondent titles.

Furthermore , descriptive statistics analysis of the demographic information of respondents in terms of frequencies, relative frequency, and percentages are shown in table A.3 (Appendix A).

4.2.5. Disruption Impacts: Data Indicators Analysis

Figure 4.11 below shows that as it demonstrates the variability of the degree of disruption extent for each indicator selected by the respondent, it facilitates

comparisons between the indicators. The highest median for disruption degree was for DI_2 (*Median* = 6). The disruption impact indicator with a wide range of scores is $DI_{5,7,8,9,10,11,\text{ and }12}$ ($R = 6$). The narrowest range of disribution was for $DI_{1,2.4,6}$ ($R = 3$), and the data here is more concentric clustered together. And DI_9 has the lowest median (*Median* = 2.5). The $DI_{5,\ 7,\ 11,\text{ and }12}$ represent the indicators with the highest variability, which shows that the data is more spread out.

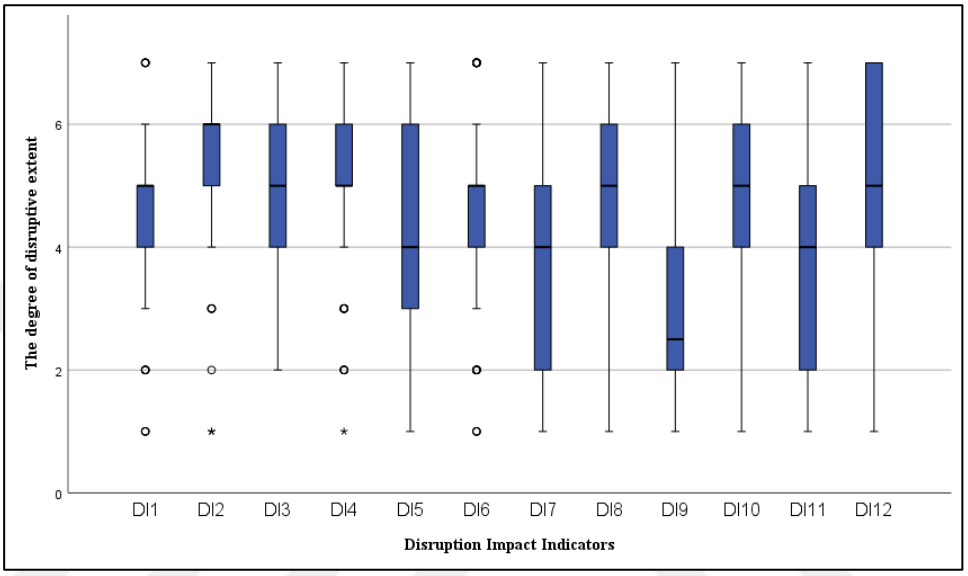

Figure 4.11: The degree of disruption extent for each disruption impact indicators.

4.2.6. Identification: Data Indicators Analysis

Figure 4.12 below represents a box plot of the degree of agreement scores assessed using a 7-point numerical rating scale (1 = strongly disagree and 7 = strongly agree) for five risk identification indicators. The highest median for the degree of agreement on the identification indicator was for I_2 (*Median* = 5.50). The identification indicator with a wide range of scores is $I_{1,2,3,4,\text{ and }5}$ ($R = 6$). The entire set of indicators has the same concentration of data and is clustered together, so there is no variation. And $I_{1,3,4,\text{ and }5}$ have the lowest median (*Median* = 5).

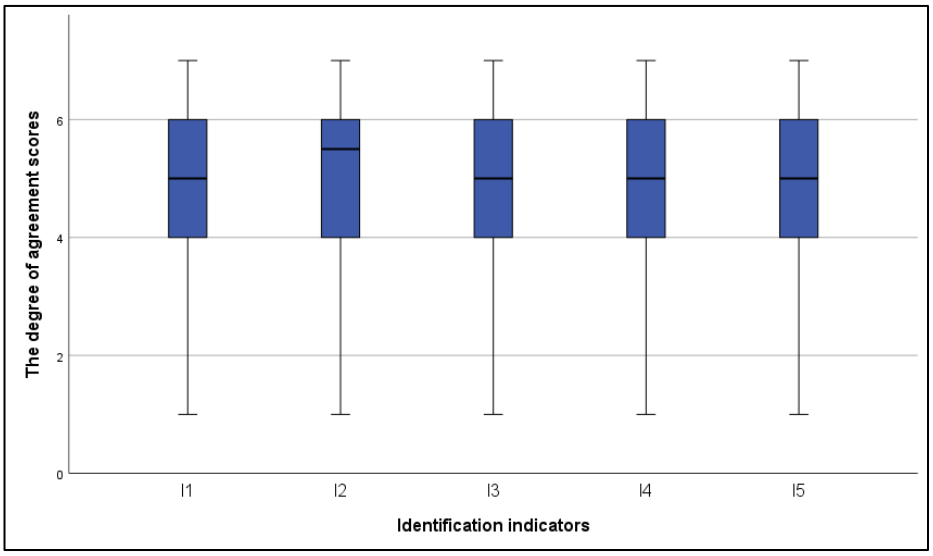

Figure 4.12: The degree of agreement scores for identification indicators.

4.2.7. Assessment: Data Indicators Analysis

Figure 4.13 below represents a box plot of the degree of agreement scores assessed using a 7-point numerical rating scale (1 = strongly disagree and 7 = strongly agree) for three risk assessment indicators. A_3 (*Median* = 6) had the greatest median for the degree of agreement on the assessment indicator. There is no variance because all of the indicators are clustered together and have the same amount of range (R = 6). The lowest median is shared by $A_{1 \text{ and } 2}$ (*Median* = 5).

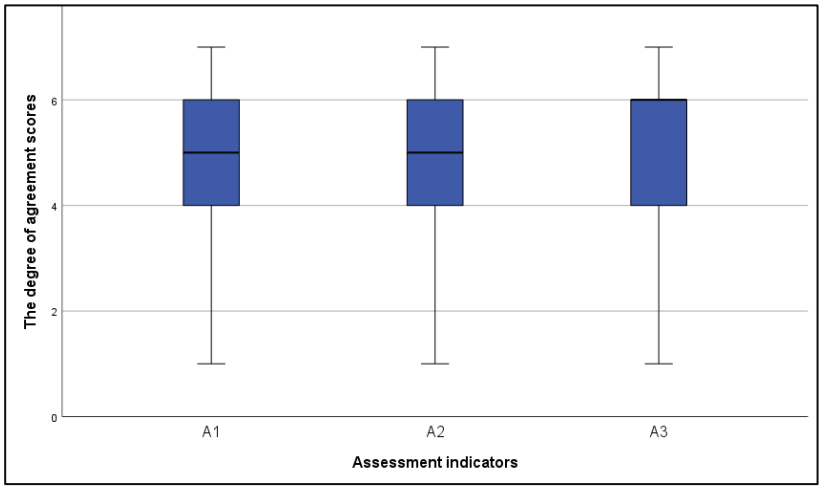

Figure 4.13: The degree of agreement scores for assessment indicators.

4.2.8. Mitigation: Data Indicators Analysis

Figure 4.14 below represents a box plot of the degree of agreement scores assessed using a 7-point numerical rating scale (1 = strongly disagree and 7 = strongly agree) for two risk mitigation indicators. $M_{1 \text{ and } 2}$ have the same median value (*Median* = 5). The variance for M_1(σ 2 = 2.28) and for M_2 (σ 2= 2.58), and have the same amount of range (*R* = 6). The mean is roughly the same for $M_{1 \text{ and } 2}$ (*M* = 4.8).

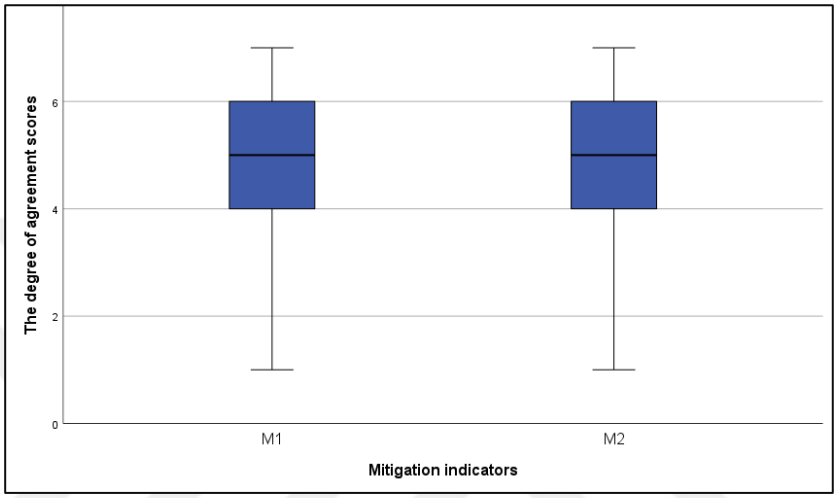

Figure 4.14: The degree of agreement scores for mitigation indicators.

4.2.9. Control: Data Indicators Analysis

Figure 4.15 below represents a box plot of the degree of agreement scores assessed using a 7-point numerical rating scale (1 = strongly disagree and 7 = strongly agree) for three risk control indicators. $C_{1,2 \text{ and } 3}$ have the same median value (*Median* = 5). The variance for the control indicators is closed in value C_1(σ 2 = 2.44), C_2 (σ 2= 2.18), and for C_3 (σ 2= 2.43), and have the same amount of range (*R* = 6). The mean is roughly the same for C_1 (*M* = 4.93), C_2 (*M* = 4.57), and for C_3 (*M* = 4.64).

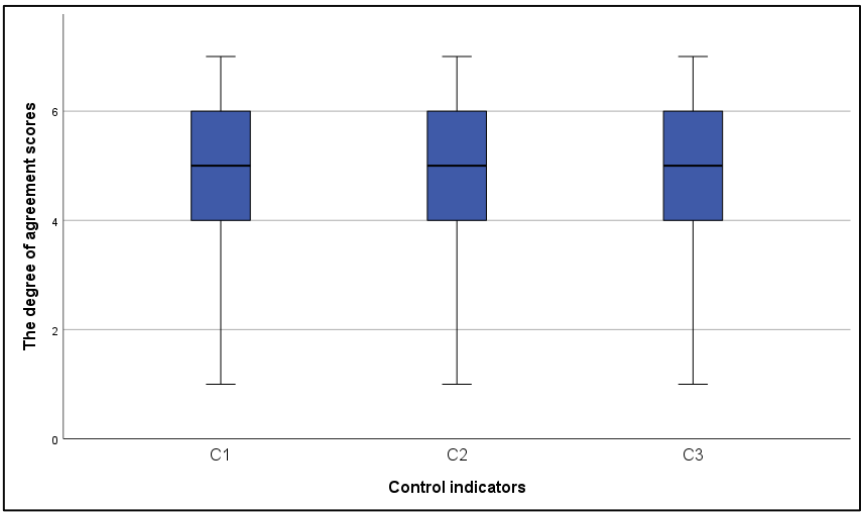

Figure 4.15: The degree of agreement scores for control indicators.

4.2.10. SC performance: Data Indicators Analysis

In the Figures 4.16 and 4.17 below represent a box plot of the degree of agreement scores assessed using a 7-point numerical rating scale (1 = strongly disagree and 7 = strongly agree) for six supply chain performance indicators, the first two columns represent the robustness indicators. the highest median value (*Median* = 6) was recorded for RO_2, whereas the median for the resilience indicators are the same with value of (*Median* = 5). The lowest median was RO_1 (*Median* = 4).

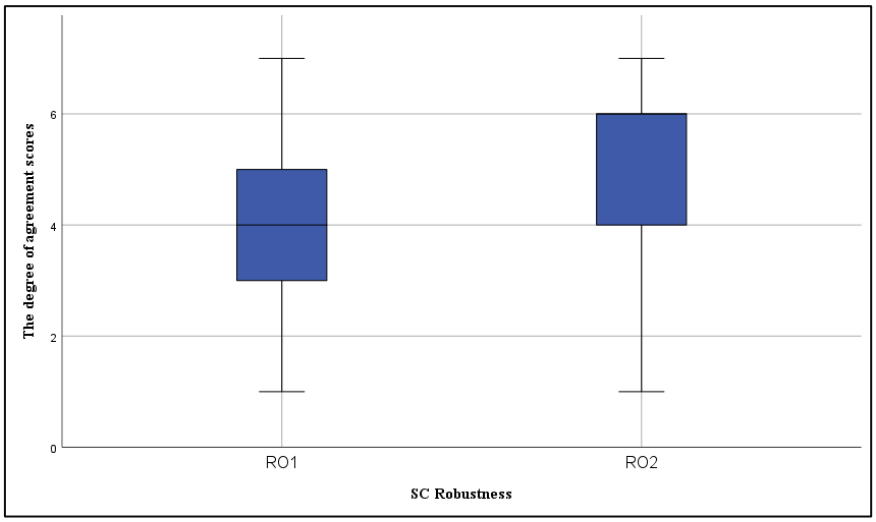

Figure 4.16: The degree of agreement scores for supply chain robustness.

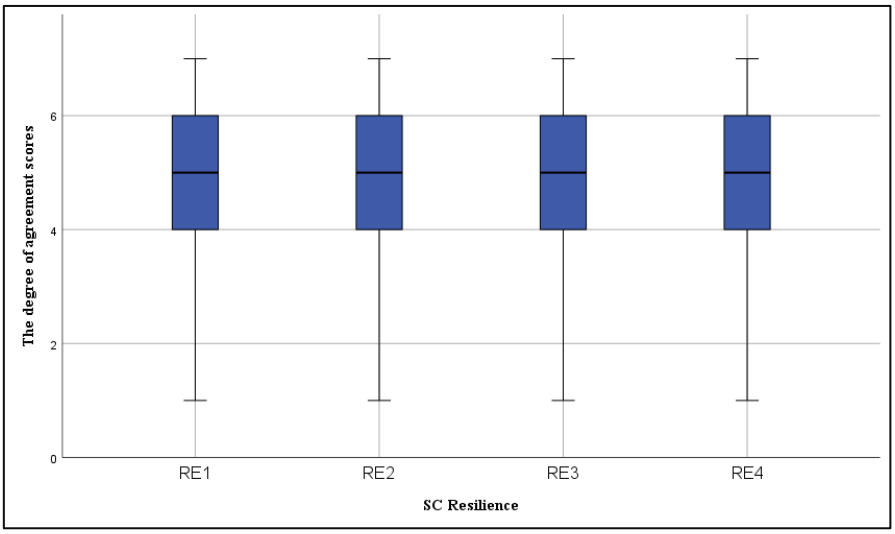

Figure 4.17: The degree of agreement scores for supply chain resilience.

Furthermore , descriptive statistics of the items construct measures in terms of mean, median, mode Std. deviation, variance, skewness, and kurtosis are shown in table A.4 (Appendix A).

4.3. Results of Model Analysis

The assessment of this structural and measurement model in the present work was done with the SmartPLS V.4.0.8. software by adopting the Confirmatory Composite Analysis (CCA) approach by using partial least squares structural equation modelling (PLS-SEM).

4.3.1. Results of Measurement Model Assessment

SmartPLS analysis is a two-step procedure. The first step in the model analysis begins by building and testing the measurement model, which shows the quality of the constructs in the study. Figure 4.18 shows how the structural and measurement models were initially set clearly as hypothesized in the theory.

The measurement model assessment starts with the evaluation of the factor loadings. This metric expresses the interdependence between each item and its construct. As part of the factor loading assessment, eight items (DI_6, DI_7, DI_8, DI_9, DI_{10}, DI_{11}, DI_{12}, and I_3) were removed from the analysis because of low standardized loadings (< 0.708) (Hair, Ringle, & Sarstedt, 2011). The outer loading results and its significance p values before items elimination is presented below in Table 4.3. Then

after the modification by the deletion of the items with rejected loadings the modified outer loading results have been uploaded and as a second step the items reliability have been calculated to provide the amount of variance shared between the individual indicator variable and its associated construct.as shown in Table 4.3, and Figure 4.19 shows the model after outerloadings modification.

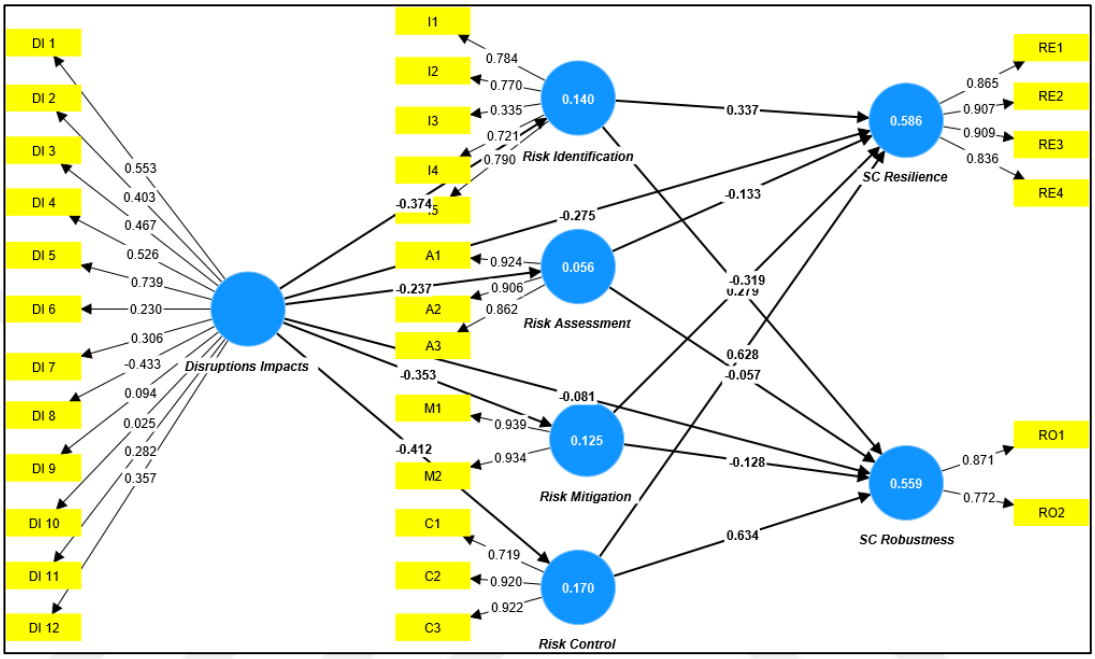

Figure 4.18: Structural and measurement model before editing by SmartPLS (v.4.0.8.).

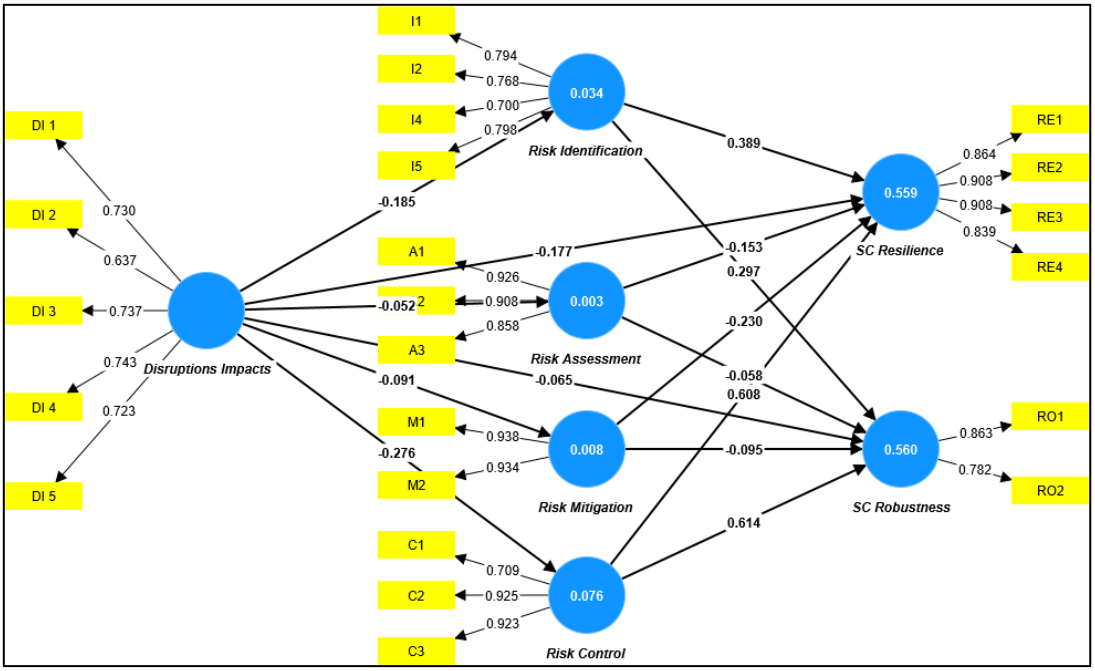

Figure 4.19: Structural model after items modification.

Table 4.3: Indicators outer loadings, significances, and reliabilities.

Constructs	Items	Loadings Before Modification	P Value	Loadings After Modification	Indicator Reliability (items)
Disruptions Impacts	DI 1	**0.553**	0.044	0.741	0.549
	DI 2	**0.403**	0.067	**0.643**	0.413
	DI 3	**0.467**	0.045	0.740	0.548
	DI 4	**0.526**	0.041	0.730	0.533
	DI 5	0.739	0.069	0.720	0.518
	DI 6	**0.230**	**0.135**		
	DI 7	**0.306**	**0.102**		
	DI 8	**-0.433**	**0.206**		
	DI 9	**0.094**	**0.352**		
	DI 10	**0.025**	**0.461**		
	DI 11	**0.282**	0.093		
	DI 12	**0.357**	0.094		
Risk Identification	I1	0.784	0.000	0.804	0.646
	I2	0.770	0.000	0.764	0.584
	I3	**0.335**	0.034		
	I4	0.721	0.000	**0.698**	0.487
	I5	0.790	0.000	0.794	0.630
Risk Assessment	A1	0.924	0.000	0.924	0.854
	A2	0.906	0.000	0.898	0.806
	A3	0.862	0.000	0.869	0.755
Risk Mitigation	M1	0.939	0.000	0.935	0.874
	M2	0.934	0.000	0.938	0.880
Risk Control	C1	0.719	0.000		
	C2	0.920	0.000	0.950	0.903
	C3	0.922	0.000	0.937	0.878
SC Resilience	RE1	0.865	0.000	0.851	0.724
	RE2	0.907	0.000	0.911	0.830
	RE3	0.909	0.000	0.906	0.821
	RE4	0.836	0.000	0.849	0.721
SC Robustness	RO1	0.871	0.000	1.000	1.000
	RO2	0.772	0.000		

The third step in the measurement model analysis is to evaluate construct reliability. The most used methods for establishing reliability are Cronbach's alpha and

composite reliability (CR). Table 4.4 below shows the reliability measures and the average variance extracted (AVE) for constructs before item modification. The results show that the CR and AVE for the DI construct are below the threshold values, which, based on the recommendation of Hair et al. (2019), should be higher than 0.70 and 0.50, respectively. The AVE for the I construct is 0.493, which is below 0.50, whereas for RO Cronbach's alpha, it is below the recommended value.

Table 4.4: Construct reliability and validity measures before modification.

	Cronbach's alpha	**Composite reliability (CR)**	**Average variance extracted (AVE)**
DI	0.816	**0.559**	**0.172**
I	0.748	0.820	**0.493**
A	0.879	0.926	0.806
M	0.860	0.934	0.877
C	0.823	0.893	0.738
RE	0.903	0.932	0.775
RO	**0.530**	0.807	0.678

Therefore, after the outer loadings' modification, the reliability and validity measures were enhanced. Both reliability criteria were higher than the recommended values of 0.70 as a rule of thumb (Hair et al., 2019). Convergent validity was acceptable because the AVE was over 0.50. The results for reliability and validity are presented in Table 4.5.

Table 4.5: Construct reliability and validity measures after modification.

	Cronbach's alpha	**Composite reliability (CR)**	**Average variance extracted (AVE)**
DI	0.785	0.84	0.512
A	0.879	0.925	0.805
C	0.877	0.942	0.89
I	0.769	0.85	0.586
M	0.86	0.934	0.877
RE	0.903	0.932	0.774
RO	1	1	1

Going through the steps reaching the 5th step in the measurement analysis. Discriminant validity which shows the distinctiveness of a construct was assessed by heterotait-monotrait ratio HTMT of correlation (Henseler et al., 2015), values below the threshold of 0.90 shows a distinct characteristic from the other constructs and kept, while those with values above 0.90 was omitted. A problem appear between the risk control and the risk mitigation constructs this issue solved by reviewing the cross-loading results as shown in Table 4.4 the difference between C1 with value 0.709 and risk mitigation construct gives a minus result and the deletion of C1 item improve the discriminant validity result. then when comparing the cross loading for the SC robustness (SCROS) with other constructs risk control, risk identification, and SC resilience (SCRES) as shown in tables from 4.6 through 4.9, RO2 item have lower cross loading and the deletion of RO2 improves the discriminant validity as well. Hence, discriminant validity is established in Table 4.5 before items deletion and the final HTMT results after modification is in Table 4.10. and Figure 4.20 shows the model after discriminant validity modification.

Table 4.6: Discriminant validity HTMT matrix before items (C1, RO2) deletion.

	DI	**A**	**C**	**I**	**M**	**RE**	**RO**
DI							
A	0.22						
C	0.292	0.74					
I	0.234	0.741	0.754				
M	0.148	0.787	**0.951**	0.621			
RE	0.406	0.325	0.685	0.673	0.373		
RO	0.354	0.612	**1.038**	**0.91**	0.696	**1.023**	

Table 4.7: Cross loading values between Risk control and Risk mitigation constructs.

	C	M
C1	**0.709**	0.86
C2	0.925	0.553
C3	0.923	0.647
M1	0.664	0.938
M2	0.732	0.935

Table 4.8: Cross loading values between SC resilience and SC robustness constructs.

	RE	RO
RE1	0.852	0.655
RE2	0.912	0.671
RE3	0.906	0.581
RE4	0.847	0.589
RO1	0.616	0.864
RO2	0.55	**0.782**

Table 4.9: Cross loading values between risk identification and SC robustness constructs.

	I	RO
I1	0.793	0.488
I2	0.768	0.397
I4	0.7	0.38
I5	0.799	0.542
RO1	0.554	0.864
RO2	0.421	**0.782**

Table 4.10: Cross loading values between risk control and SC robustness constructs.

	C	RO
C1	0.709	0.453
C2	0.925	0.724
C3	0.923	0.603
RO1	0.636	0.864
RO2	0.521	**0.782**

Table 4.11: Final HTMT results after modification.

	DI	**A**	**C**	**I**	**M**	**RE**	**RO**
DI							
A	0.22						
C	0.302	0.569					
I	0.234	0.741	0.704				
M	0.148	0.787	**0.733**	0.621			
RE	0.406	0.325	0.756	0.673	0.373		
RO	0.22	0.369	**0.677**	**0.622**	0.49	**0.647**	

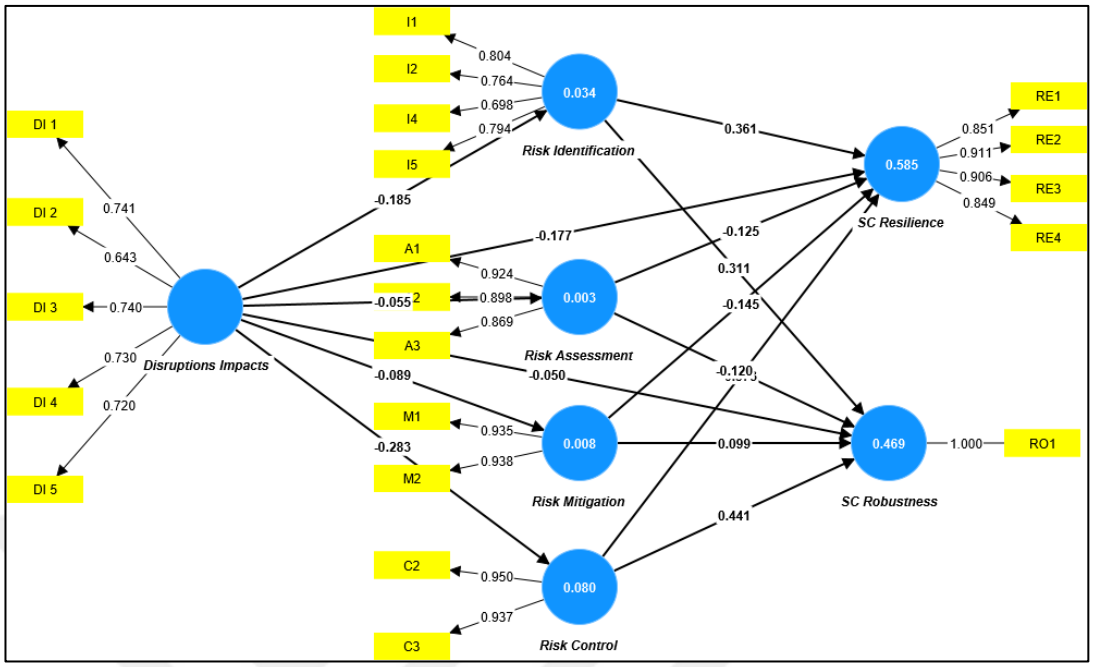

Figure 4.20: Structural model after discriminant validity modification.

4.3.2. Results of Structural Model Assessment

The first step in structural model assessment is done by assessing the multicollinearity issues of the inner model among the variables. Which mainly check the relationships if the exogenous variables measure the same attribute of the endogenous variable, then it is considered as a multicollinearity issue. The variance inflation factor VIF values is used for this examination. Table 4.12 illustrates the value of the collinearity statistic VIF of the inner model. For SC disruption impacts, SCRM practices constructs, SC resilience, and SC robustness. The results with VIF values under 3 which represents no multicollinearity issues.

Table 4.12: Inner collinearity statistics (VIF) values.

	DI	I	A	M	C	RE	RO
DI		1.000	1.000	1.000	1.000	1.113	1.113
I						1.855	1.855
A						2.265	2.265
M						2.427	2.427
C						2.130	2.130
RE							
RO							

Since there is no issue with the collinearity. An evaluation of the significance of the hypothesis relationship by running the bootstrapping with 10.000 subsamples and choosing the error probability as 0.10 corresponds to 90% confidence intervals, and since the concern is about a specific relationship whether it is a positive or negative relationship thus the test type was chosen to be one-tailed.

The results show negative and significant direct relationship between disruptions impacts and SC risk identification, SC risk control and SC resilience. Such findings demonstrate the negative impact of COVID-19 on companies SCRM practices and their capability to recover performance after absorbing the disruption effects. Therefore, H1a, H1d and H2 are supported. Conversely, no significant direct effect of distribution impacts was found either on SCROS or SC risk assessment and mitigation. Hence, H1b, H1c, and H3 were rejected.

Moreover, the findings indicate that only SC risk identification and control had positive and significant effect on SCRES and SCROS. On the other hand, SC risk assessment and mitigation have a negative insignificant effect on SC resilience. And SC risk assessment has a negative insignificant effect on SC robustness, while SC risk mitigation has a positive insignificant effect on SC robustness. Consequently, H4.a, H5a, H4.d and H5d are supported. Therefore, H4b, H5b, and H4c and H5c were rejected.

H1.a evaluates whether COVID-19 disruptions impact influence negatively risk identification practice. The results revealed that COVID-19 disruptions impact has a significant and negative impact on risk identification ($\beta = -0.185$, $t = 1.342$, $P < 0.10$). Hence, H1.a was supported.

H1.b evaluates whether COVID-19 disruptions impact influence negatively risk assessment practice. The results revealed that COVID-19 disruptions impact has a negative impact on risk assessment but an insignificant impact ($\beta = -0.055$, $t = 0.395$, $P > 0.10$). Hence, H1.b was not supported.

H1.c evaluates whether COVID-19 disruptions impact influence negatively risk mitigation practice. The results revealed that COVID-19 disruptions impact has a negative impact on risk mitigation but an insignificant impact ($\beta = -0.089$, $t = 0.738$, $P > 0.10$). Hence, H1.c was not supported.

H1.d evaluates whether COVID-19 disruptions impact influence negatively risk control practice. The results revealed that COVID-19 disruptions impact has a significant and negative impact on risk control (β = -0.283, t = 2.608, P = 0.005). Hence, H1.d was supported.

H2 evaluates whether COVID-19 disruptions impact influence negatively SC resilience. The results revealed that COVID-19 disruptions impact has a significant and negative impact on SCRES (β = -0.177, t = 2.460, P = 0.007). Hence, H2 was supported.

H3 evaluates whether COVID-19 disruptions impact influence negatively SC robustness. The results revealed that COVID-19 disruptions impact has a negative but insignificant impact on SCROS (β = -0.050, t = 0.584, P > 0.10). Hence, H3 was not supported.

H4.a evaluates whether risk identification influence positively SC resilience. The results revealed that risk identification has a significant and positive impact on SCRES (β = + 0.361, t = 3.550, P = 0.000). Hence, H4.a was supported.

H4.b evaluates whether risk assessment influence positively SC resilience. The results revealed that risk assessment has an insignificant and negative impact on SCRES (β = - 0.125, t = 0.852, P > 0.10). Hence, H4.b was not supported.

H4.c evaluates whether risk mitigation influence positively SCRES. The results revealed that risk mitigation has an insignificant and negative impact on SCRES (β = - 0.145, t = 1.000, P > 0.10). Hence, H4.c was not supported.

H4.d evaluates whether risk control influence positively SC resilience. The results revealed that risk control has a significant and positive impact on SCRES (β = + 0.573, t = 6.318, P = 0.000). Hence, H4.d was supported.

H5.a evaluates whether risk identification influence positively SC robustness. The results revealed that risk identification has a significant and positive impact on SCROS (β = + 0.311, t = 2.838, P = 0.002). Hence, H5.a was supported.

H5.b evaluates whether risk assessment influence positively SC robustness. The results revealed that risk assessment has an insignificant and negative impact on SCROS (β = - 0.120, t = 0.971, P > 0.10). Hence, H5.b was not supported.

H5.c evaluates whether risk mitigation influence positively SC robustness. The results revealed that risk mitigation has a positive but insignificant impact on SCROS (β = + 0.099, t = 0.608, P > 0.10). Hence, H5.c was not supported.

H 5.d evaluates whether risk control influence positively SC robustness. The results revealed that risk control has a significant and positive impact on SCROS (β = + 0.441, t = 3.533, P = 0.000). Hence, H5.d was supported.

The Hypotheses testing results are summarized in Table 4.13. The structural model is presented in Figure 4.21.

Table 4.13: Path coefficient direct relationship results

Hypothesis	β	T statistics	P values	Results
H2: DI -> RE	- 0.177	2.460	0.007	Supported
H3: DI -> RO	- 0.050	0.584	**0.279**	Not supported
H1.a: DI -> I	- 0.185	1.342	0.090	Supported
H1.b: DI -> A	- 0.055	0.395	**0.347**	Not supported
H1.c: DI -> M	- 0.089	0.738	**0.230**	Not supported
H1.d: DI -> C	- 0.283	2.608	0.005	Supported
H4.a: I -> RE	+ 0.361	3.550	0.000	Supported
H5.a: I -> RO	+ 0.311	2.838	0.002	Supported
H4.b: A -> RE	- 0.125	0.852	**0.197**	Not supported
H5.b: A -> RO	- 0.120	0.971	**0.166**	Not supported
H4.c: M -> RE	- 0.145	1.000	**0.159**	Not supported
H5.c: M -> RO	+ 0.099	0.608	**0.272**	Not supported
H4.d: C-> RE	+ 0.573	6.318	0.000	Supported
H5.d: C -> RO	+ 0.441	3.533	0.000	Supported

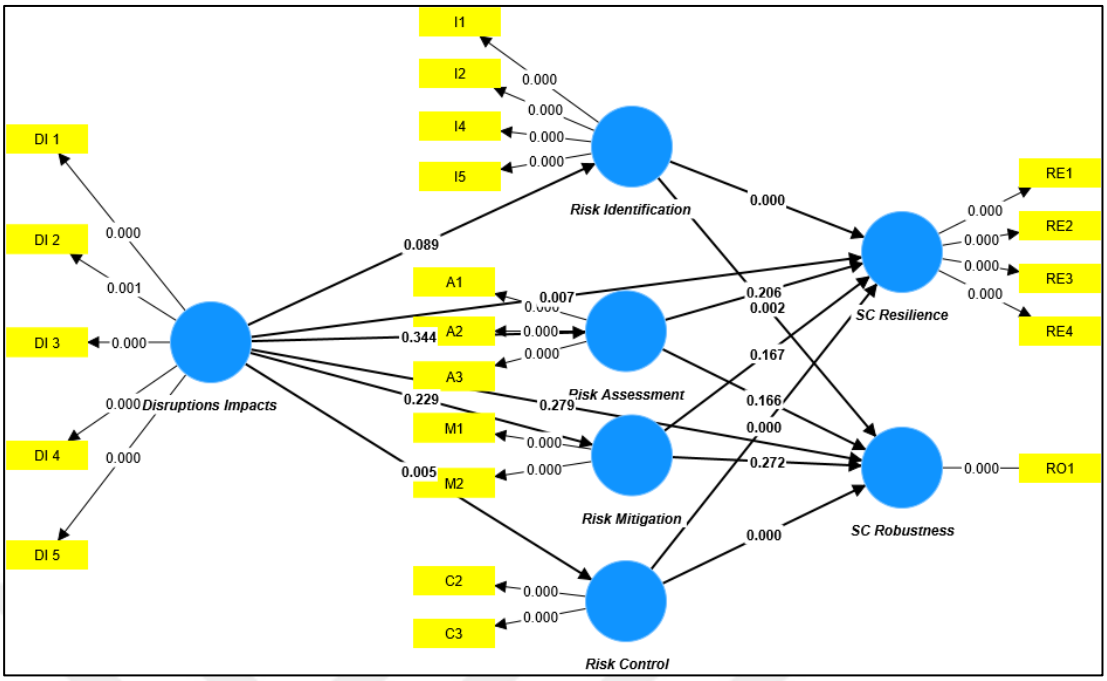

Figure 4.21: Structural model path coefficients results.

Next step in assessing the quality of the structural model is to compute the R-square statistics which represent the coefficients of determination (Hair et al., 2012), and it display the variance in the endogenous variable explained by the exogenous variables as whole in the model assessment (Pesamaa et al., 2010). Several researchers had suggested an acceptable level for R-square, depending on the research context, Cohen (1988) suggestion was adopted that R-square value with 0.26 is substantial, 0.13 moderate, and 0.02 as weak.

R-square results have been extracted without any path modification. As presented in table 4.14, which shows the coefficients of determination and their significance. all the values found to be significant, excluding risk identification, risk assessment, and risk mitigation which have been considered insignificant with p values greater than 0.01.

SC disruption impacts explain two practices of SCRM that have a weak R-square (0.080 and 0.034) according to Cohen (1988); whereas two of them (Assessment and Mitigation) has a limited R-square (0.003 and 0.008) respectively. These low values have been justified by the literature with the following statements, first as a rule of thumb R-square value depends on the field of the study and discipline, thus it changes from industry to industry. Secondly, it increases with additional predictor constructs (Hair et al, 2019), and since there is only single independent variable explains those

practices, it is expected to have those low values. On the other hand, the four SCRM practices explain 0.585 of SCRES and 0.469 of SCROS which is considered as substantial for both.

Table 4.14: R-Square

Construct	R-square	P values	Results
I	0.034	0.256	weak
A	0.003	0.467	unacceptable
M	0.008	0.397	unacceptable
C	0.080	0.085	weak
RE	0.585	0.000	Substantial
RO	0.469	0.000	Substantial

The fourth step in measuring the predictive ability of the structural model is accomplished by determining the effect size f-square. To study how the removing of the exogenous variable SC disruption impacts can affect the dependent variable. Depending on f-square values in table 4.15 below, dropping the SC disruption impacts variable that clarifies the endogenous variables (risk assessment, risk mitigation, and SC robustness) has comparatively no effect size on R-square as the value is less than the threshold of 0.02. while f-square values show that dropping the exogenous variable SC disruption impacts that clarifies the endogenous variables (risk control, risk identification, and SC resilience) has comparatively small to medium effect size since the values between 0.02-0.15. Moreover, the risk assessment has no effect on SCRES and SCROS as the value is less than 0.02. While dropping the risk control that clarifies SCRES and SCROS has a large to medium effects the $f^2 = 0.371$, and 0.172 respectively. Also, the results show that dropping the risk identification that clarifies SCROS and SCRES has a weak to medium effects the $f^2 = 0.098$, and 0.169 respectively. Dropping the risk mitigation which clarifies the SCRES will have weak effect, whereas no effect on the SC robustness. A low effect size does not always mean that an underlying mediator effect is negligible, according to chin et al. (2003), since even a tiny interaction effect might be significant in extreme circumstances. These findings confirm the interpreted Coefficient of determination results' recommendations to include additional exogenous variables, which primarily explain risk assessment and mitigation, since there is a single exogenous variable in the model.

Table 4.15: Effect sizes for path and their significance

path	f-Square	P values
DI -> A	0.003	**0.472**
DI -> C	0.087	**0.129**
DI -> I	0.035	**0.291**
DI -> M	0.008	**0.408**
DI -> RE	0.068	**0.126**
DI -> RO	0.004	**0.428**
A -> RE	0.017	**0.378**
A -> RO	0.012	**0.356**
C ->RE	0.371	0.021
C -> RO	0.172	0.067
I -> RE	0.169	0.063
I -> RO	0.098	0.080
M -> RE	0.021	**0.357**
M -> RO	0.008	**0.429**

Finally, the values of the indicator of the quality of the model adjustment are estimated (Q^2) from PLS-Predict tool in SMARTPLS choosing the number of folds equal to 3 since the recommendation of Hair et al., (2019) for a minimum size for the holdout sample would be N = 30, and as the total sample size is 102 thus a minimum subsample of 34 could be reached when K=3. The implied number of repetitions is 100. As rule of thumb values greater than 0 should be obtained (Hair et al., 2019).

The interpretation of Table 4.16 shows the results of Q^2 for the endogenous constructs shows that the risk control, SC resilience, and SC robustness which have values greater than the threshold suggested, and it could be included in the model as it has a sufficient predictive relevance. Whereas risk identification, risk assessment, and risk mitigation below zero and would lack a good predictive relevance.

Table 4.16: Predictive relevance validity (Q^2) indicators.

Construct	Q^2predict	RMSE	MAE
I	-0.012	1.034	0.839
A	-0.024	1.049	0.820
M	-0.027	1.047	0.804
C	0.032	1.010	0.811
RE	0.102	0.986	0.758
RO	0.019	1.018	0.815

Final step, an assessment of the model's predictive capability the PLSpredict algorithm was utilized which was supported by Shmueli et al., (2016). The execution of this algorithm involves dividing the total sample into an equal sized sample and then a single holdout sample is picked each trail to predict its predictive performance by the rest training sample (Shmueli et al., 2016). To assess this, the 3 number of folds (k=3) cross validation with 100 number of repetitions (r=100) to measure the predicted validity of the endogenous indicators. Two predictive error metrics were considered that is root means squared error of predictions (RMSE) and mean absolute error (MAE). To measure the predictive quality of the PLS path model the error metrics' values are compared to the linear model (LM) prediction naïve benchmark. As a rule of thumb, the higher the values of PLS model than the sample model (LM) indicates that the model lacks predictive power. It can be seen from table 4.17 the analysis of the PLSpredict that the majority of the RMSE values for PLS model 14 items out of 16 items were higher than the LM, which demonstrates that the PLS model has sufficiently high predictive power. 11 out of 16 items were with higher predictive error for MAE metric than the LM, which is shown in table 4.18. The interpretation supports the high predictive power of the model founded previously by the RMSE metric.

Table 4.17: RMSE PLSpredict results

Items	PLS-SEM_RMSE	LM_RMSE	Δ RMSE (PLS – LM)
I1	1.461	1.505	-0.044
I2	1.411	1.435	-0.024
I4	1.389	1.433	-0.044
I5	1.514	1.508	**0.006**
A1	1.366	1.380	-0.014
A2	1.402	1.396	0.006
A3	1.479	1.522	-0.043
M1	1.542	1.582	-0.040
M2	1.641	1.683	-0.042
C2	1.460	1.522	-0.062
C3	1.554	1.605	-0.051
RE1	1.280	1.257	**0.023**
RE2	1.396	1.430	-0.034
RE3	1.364	1.395	-0.031
RE4	1.402	1.452	-0.050
RO1	1.505	1.561	-0.056

Table 4.18: MAE PLSpredict results

Item	PLS-SEM_MAE	LM_MAE	Δ MAE (PLS – LM)
I1	1.220	1.233	-0.013
I2	1.168	1.186	-0.018
I4	1.040	1.084	-0.044
I5	1.241	1.193	**0.048**
A1	1.093	1.090	**0.003**
A2	1.138	1.100	**0.038**
A3	1.208	1.208	**0.000**
M1	1.249	1.306	-0.057
M2	1.308	1.327	-0.019
C2	1.188	1.202	-0.014
C3	1.252	1.269	-0.017
RE1	1.000	0.951	**0.049**
RE2	1.105	1.113	-0.008
RE3	1.049	1.058	-0.009
RE4	1.126	1.166	-0.040
RO1	1.210	1.226	-0.016

In Table 4.19, the results reveal the mediating role of SCRM practices and the prominent role they play in fostering supply chain resilience and robustness. As the indirect effect have provide a significant effect for both the resilience and robustness of the SC.

An additional analysis has been conducted. known as an importance performance map analysis (IPMA), to highlight the constructs with a key role in predicting SC resilience and robustness. The results in table 4.20 shows that risk assessment construct has the biggest performance in both of SC resilience and robustness. Furthermore, it is risk control and identification that has the biggest importance in building SC robustness with respective values of 0.441 and 0.311. Accordingly, increasing SC risk control by one unit, from 60.002 to 61.002, would raise robustness by 0.441 points, while increasing SC risk identification by one unit, would enhance robustness by 0.311 points. As a result, firms that seek to enhance their SC robustness need to concentrate on how they identify and control SC risks. in terms of SC resilience, SC risk control and identification are also with the greatest important. Therefore, the priority in SCRES for firms should be improving risk identification and

control. Figures 4.21 and 4.22 below show the graphical description for the PLS-IPMA results for both SCRES and SCROS respectively.

Table 4.19: Total, Direct, and Indirect hypothesis test results

Hypothesis test	Direct effect β	P values	Indirect effect β	P value	Total effect β	P value
H2: DI -> RE	- 0.177	0.007	- 0.209	0.005	- 0.387	0.000
H3: DI -> RO	- 0.050	**0.279**	- 0.185	0.015	- 0.235	0.011
H1.a: DI -> I	- 0.185	0.090			- 0.185	0.090
H1.b: DI -> A	- 0.055	**0.347**			- 0.055	**0.347**
H1.c: DI -> M	- 0.089	**0.230**			- 0.089	**0.230**
H1.d: DI -> C	- 0.283	0.005			- 0.283	0.005
H4.a: I -> RE	+ 0.361	0.000			+0.361	0.000
H5.a: I -> RO	+ 0.311	0.002			+0.311	0.002
H4.b: A -> RE	- 0.125	**0.197**			- 0.125	**0.197**
H5.b: A -> RO	- 0.120	**0.166**			- 0.120	**0.166**
H4.c: M -> RE	- 0.145	**0.159**			- 0.145	**0.159**
H5.c: M -> RO	+ 0.099	**0.272**			+0.099	**0.272**
H4.d: C-> RE	+ 0.573	0.000			+0.573	0.000
H5.d: C -> RO	+ 0.441	0.000			+0.441	0.000

Table 4.20: PLS-IPMA results

Constructs	SC Resilience		SC Robustness	
	Importance	Performance	Importance	Performance
DI	-0.387	60.067	-0.235	60.067
I	0.361	64.542	0.311	64.542
A	-0.125	70.675	-0.120	70.675
M	-0.145	64.386	0.099	64.386
C	0.573	60.002	0.441	60.002

As both Figures 4.22 and 4.23 show an IPMA matrix that consists of four quadrants. Items that fall in Quadrant I represent "keep up the good work," while items in Quadrant II represent "possible overkill," "low priority" items are located in Quadrant III, and Quadrant IV represents "concentrate here."

In figure 4.22, items falling in Quadrant I have both high performance and high importance; RI and RC items are located in this quadrant and considered the major strengths of the firm's resilience; thus, those items should always be maintained and leveraged. The rest of the items (RA, DI, and risk mitigation) fall in Quadrant II, which is characterized by low importance but high performance for the resilience construct. Because these items are regarded as the next competitive advantages, the firm should avoid devoting excessive resources to them. In Figure 4.23, shows the relative importance of the constructs in explaining robustness in the structural model. It shows the same results as explained in Figure 4.22.

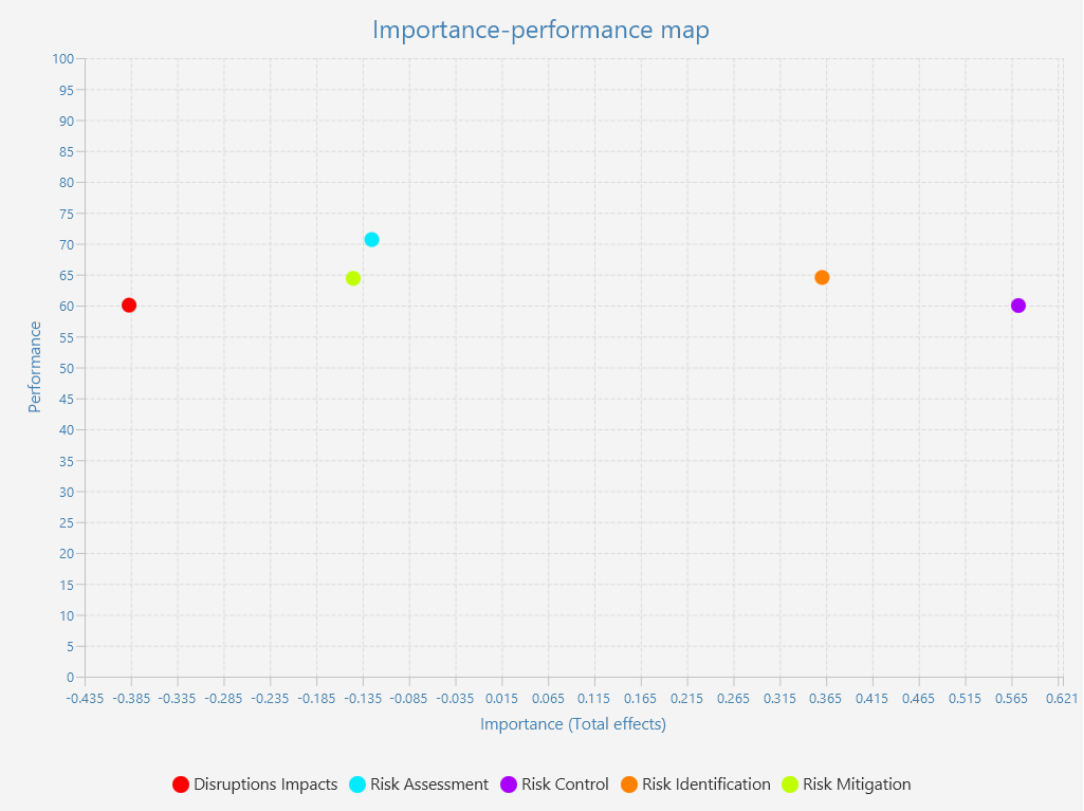

Figure 4.22: SC resilience Importance-Performance map.

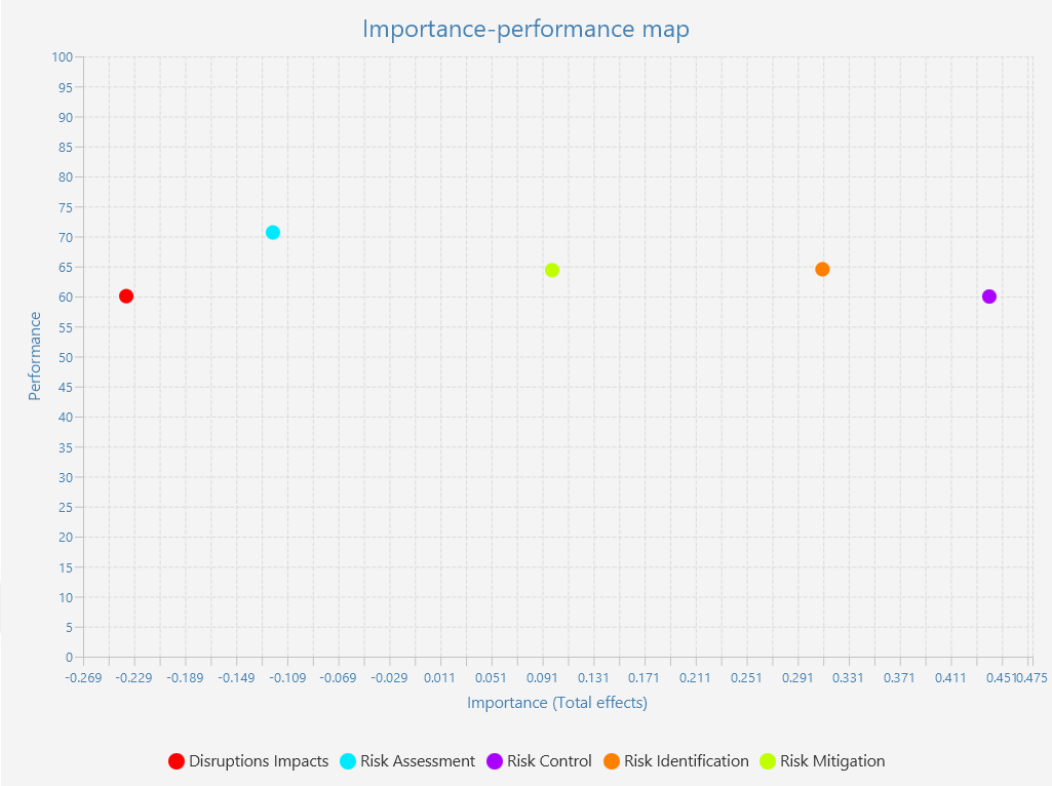

Figure 4.23: SC robustness Importance-Performance map.

5. CONCLUSION

The sudden emergence of the global epidemic of COVID-19 has affected several global operations across numerous industries. Over time, the supply chain has been affected by a variety of unexpected events, including natural disasters such as volcanoes, earthquakes, and epidemics. However, the recent epidemic COVID-19 had new effects that the world had never experienced before. This forced several risk managers to improvise and take quick decisions to maintain the performance of the supply chain (SC).

This inspired the study to investigate the impact of COVID-19 epidemic's disruption impacts on the supply chain risk management's (SCRM's) practices and the effect of their practices on SC's resilience and robustness. The purpose of this study is to understand the impact of COVID -19 on a Turkish pharmaceutical supply chain and adopt a model that illustrates and clarifies this relationship.

The data collected via constructed questionnaire were analyzed using Confirmatory Composite Analysis (CCA) based on Partial Least Square-Structural Equation Modeling (PLS-SEM) to confirm the reflective measurement model using SmartPLS V. 4.0.8 statistical software.

Results show that COVID-19 disruptions impact affect negatively how firms identify and control supply chain risk (SCR). Due to the amplitude of sudden disturbances at the global scale that few firms were able to predict in advance, COVID-19 have affected mainly SC resilience. This demonstrates the negative impact of the epidemic on the SCRM practices and their abilities to regain their SC performance after absorbing the disruption effects. However, it is found that SC robustness was not directly affected by disruption impacts as most of the firms seem to think that they will be able to maintain its planned performance after disruption. Therefore, H1a, H1d and H2 hypotheses are supported. Conversely, there was no significant direct effect of COVID-19 impacts on SC robustness or SC risk assessment and mitigation. Hence, H1b, H1c, and H3 were rejected. Furthermore, the findings reveal the mediating role of SCRM practices and the prominent role they play in fostering supply chain resilience and robustness.

Moreover, the findings indicate that only SC risk identification and control had positive and significant effect on SC resilience and SC robustness. On the other hand,

SC risk assessment and mitigation have a negative insignificant effect on SC resilience. And SC risk assessment has a negative insignificant effect on SC robustness, while SC risk mitigation has a positive insignificant effect on SC robustness. Consequently, H4.a, H5a, H4.d and H5d are supported. Therefore, H4b, H5b, and H4c and H5c were rejected.

The importance performance map analysis (IPMA) provides an insight for recommendations that supply chain risk managers can reconsider. As a result, firms that seek to enhance their SC robustness and SC resilience need to concentrate on how they identify and control SC risks since these practices are with the greatest importance in building a robust and resilient supply chain.

The study faces several limitations that offer further researchers to develop. First, the study chooses the Turkish pharmaceutical supply chain sector to be adopted, and as a policy some pharmaceutical companies do not provide an access to some of the most crucial data. Thus, during the mailing some of the respondents have notified about their conservative answers to some questions according to their policy. Second, there was no access to longitudinal data; the research was carried out in a short span of time, which might provide useful insight regarding the interaction among disruption impacts, SCRM practices, SC resilience and robustness in long-term so it is recommended to widen the study for future researches.

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APPENDIX A_

Table 0.1: Variables with their scale type

Variable	Scale Type
Number of employees	Nominal
Experience/age of company (in years)	Nominal
Respondent titles	Nominal
Work experience in the industry:	Nominal
Work experience in the current company	Nominal
SC Disruption Impact	Ordinal
Identification	Ordinal
Assessment	Ordinal
Mitigation	Ordinal
Control	Ordinal
SC performance	Ordinal

Table A.2: Standard error of each respondent

Statistics	Std. Deviation
respondent1	1.430
respondent2	1.644
respondent3	1.060
respondent4	1.319
respondent5	2.036
respondent6	0.749
respondent7	0.814
respondent8	1.313
respondent9	1.385
respondent10	1.807
respondent11	0.964
respondent12	0.815
respondent13	0.856
respondent14	1.411
respondent15	0.477
respondent16	1.473
respondent17	1.904
respondent18	1.909
respondent19	1.690
respondent20	1.432
respondent21	0.769
respondent22	1.025
respondent23	1.256
respondent24	1.979

respondent25	1.469
respondent26	1.798
respondent27	1.131
respondent28	1.408
respondent29	1.153
respondent30	1.720
respondent31	0.811
respondent32	2.493
respondent33	2.006
respondent34	1.492
respondent35	1.355
respondent36	1.543
respondent37	1.504
respondent38	1.838
respondent39	1.241
respondent40	0.990
respondent41	1.460
respondent42	1.278
respondent43	1.502
respondent44	1.961
respondent45	1.551
respondent46	0.845
respondent47	1.687
respondent48	0.930
respondent49	1.589
respondent50	0.445
respondent51	1.472
respondent52	1.653
respondent53	1.261
respondent54	1.380
respondent55	1.820
respondent56	1.160
respondent57	2.148
respondent58	1.532
respondent59	0.428
respondent60	0.454
respondent61	0.564
respondent62	0.929
respondent63	1.194
respondent64	1.283
respondent65	1.358
respondent66	2.080
respondent67	1.667
respondent68	2.012
respondent69	1.480
respondent70	1.308
respondent71	1.378

respondent72	0.922
respondent73	1.958
respondent74	2.425
respondent75	1.321
respondent76	1.707
respondent77	1.683
respondent78	1.961
respondent79	1.463
respondent80	2.500
respondent81	1.551
respondent82	1.539
respondent83	0.497
respondent84	0.925
respondent85	0.929
respondent86	1.316
respondent87	1.234
respondent88	1.352
respondent89	1.476
respondent90	0.839
respondent91	0.486
respondent92	0.752
respondent93	1.440
respondent94	1.454
respondent95	2.128
respondent96	1.722
respondent97	0.425
respondent98	1.494
respondent99	1.726
respondent100	1.880
respondent101	1.039
respondent102	2.349

Table A.3: Descriptive statistics analysis

Characteristics of respondents (*N* = 102)	Frequency	Relative Frequency	Percentage
Number of employees			
<10	7	0.069	6.9%
10-49	14	0.137	13.7%
50-199	14	0.137	13.7%
200-500	14	0.137	13.7%
>500	53	0.520	52%
Total	102	1	100%
Experience/age of company (in years)			
<10 year	23	0.225	22.5%
10-19 year	18	0.176	17.6%
20-29 year	12	0.118	11.8%
30-50 year	13	0.127	12.7%
>50 year	36	0.353	35.3%
Total	102	1	100%
Respondent titles			
Warehouse Manager	7	0.069	6.9%
Export Sales Manager	9	0.088	8.8%
Logistics Manager	9	0.088	8.8%
Purchasing Manager	30	0.294	29.4%
Supply Chain Manager	47	0.461	46.1%
Total	102	1	100%
Work experience in the industry:			
5 years or less	20	0.196	19.6%
6 -10 year	18	0.176	17.6%
11 years or more	64	0.627	62.7%
Total	102	1	100%
Work experience in the current company			
5 years or less	71	0.696	69.6%
6 - 10 year	16	0.157	15.7%
11 years or more	15	0.147	14.7%
Total	102	1	100%

Table 0.4: Descriptive statistics of items construct measures.

Statistics	Mean	Median	Mode	Std. Deviation	Variance	Skewness		Kurtosis	
						Statistic	Std. Error of Skewness	Statistic	Std. Error of Kurtosis
DI 1	4.54	5	5	1.34	1.795	-0.463	0.239	0.285	0.474
DI 2	5.52	6	6	1.295	1.678	-1.187	0.239	1.843	0.474
DI 3	5.00	5	4[a]	1.16	1.347	-0.078	0.239	-0.634	0.474
DI 4	5.15	5	6	1.262	1.592	-0.946	0.239	0.942	0.474
DI 5	4.05	4	4	1.743	3.037	-0.214	0.239	-0.863	0.474
DI 6	4.56	5	5	1.466	2.15	-0.349	0.239	-0.083	0.474
DI 7	3.68	4	4	1.707	2.914	-0.053	0.239	-0.951	0.474
DI 8	4.95	5	6	1.793	3.215	-0.755	0.239	-0.449	0.474
DI 9	3.03	2.5	2	1.76	3.098	0.677	0.239	-0.525	0.474
DI 10	4.71	5	5	1.755	3.081	-0.435	0.239	-0.59	0.474
DI 11	3.74	4	1	2.005	4.018	0.012	0.239	-1.335	0.474
DI 12	5.08	5	7	1.733	3.004	-0.74	0.239	-0.165	0.474
I1	4.73	5	6	1.457	2.122	-0.351	0.239	-0.472	0.474
I2	5.2	5.5	6	1.4	1.961	-0.667	0.239	-0.047	0.474
I3	4.74	5	4	1.502	2.256	-0.304	0.239	-0.328	0.474
I4	4.96	5	5	1.349	1.82	-0.766	0.239	0.971	0.474
I5	4.67	5	4[a]	1.511	2.284	-0.344	0.239	-0.452	0.474
A1	5.26	5	5	1.349	1.82	-0.694	0.239	0.422	0.474
A2	5.27	5	6	1.373	1.884	-0.722	0.239	0.573	0.474
A3	5.19	6	6	1.454	2.113	-0.805	0.239	0.228	0.474
M1	4.88	5	6	1.511	2.283	-0.534	0.239	-0.416	0.474
M2	4.84	5	6	1.609	2.589	-0.7	0.239	-0.163	0.474
C1	4.93	5	6	1.562	2.441	-0.71	0.239	-0.089	0.474
C2	4.57	5	5	1.479	2.188	-0.155	0.239	-0.669	0.474
C3	4.64	5	5	1.559	2.431	-0.413	0.239	-0.456	0.474
RO1	4.29	4	4	1.506	2.269	-0.268	0.239	-0.379	0.474
RO2	5.22	6	6	1.376	1.894	-0.794	0.239	0.2	0.474
RE1	5.14	5	6	1.313	1.724	-0.955	0.239	1.527	0.474
RE2	4.89	5	6	1.448	2.097	-0.706	0.239	0.231	0.474
RE3	5.00	5	5	1.428	2.04	-0.77	0.239	0.551	0.474
RE4	4.85	5	5	1.431	2.047	-0.274	0.239	-0.346	0.474
a. Multiple modes exist. The smallest value is shown									

APPENDIX B_

Table B.1: Survey items information before factor modifying

Constructs	Items	Indicator	Reference
SC Disruption Impacts	DI1	How did COVID-19 disruption negatively affect overall efficiency of operations.	(El Baz & Ruel, 2020)
	DI2	How did COVID-19 disruption negatively affect lead time for delivery (delivery reliability).	
	DI 3	How did COVID-19 disruption negatively affect purchasing costs for supply.	
	DI 4	To what extent has your firm during COVID-19 experienced a negative impact in supply chain management due poor logistics performance of logistics service providers.	(Parast, 2020)
	DI 5	To what extent has your firm during COVID-19 experienced a negative impact in supply chain management due to capacity fluctuations or shortages on the supply markets.	
	DI 6	To what extent has your firm during COVID-19 experienced a negative impact in supply chain management due to unanticipated or very volatile demand.	
	DI 7	To what extent has your firm during COVID-19 experienced a negative impact in supply chain management due to unusual customer payment delays.	
	DI 8	To what extent has your firm during COVID-19 experienced a negative impact in supply chain management due to request from the customer to expedite pending order (s).	
	DI 9	To what extent has your firm during COVID-19 experienced a negative impact in supply chain management due to Drop in customer satisfaction.	
	DI 10	To what extent has your firm during COVID-19 experienced a negative impact in supply chain management due to drop in delivery speed: Time between order receipt and customer delivery.	
	DI 11	To what extent has your firm during COVID-19 experienced a negative impact in supply chain management due to drop in overall product quality.	
	DI 12	To what extent has your firm during COVID-19 experienced a negative impact in supply chain management due to drop in overall customer service levels.	
	DI 13		

		To what extent has your firm during COVID-19 experienced a negative impact in supply chain management due to drop in market share.	
	DI14	To what extent has your firm during COVID-19 experienced a negative impact in supply chain management due to drop in average selling price (high performance means higher average price).	
	DI15	To what extent has your firm during COVID-19 experienced a negative impact in supply chain management due to drop in overall competitive position.	
	DI16	How did COVID-19 disruption negatively affect choice of mode of transportation	(Shahbaz et al., 2019)
	DI7	How did COVID-19 disruption negatively affect packaging and marking details	
	DI18	How did COVID-19 disruption negatively affect choice of communication	
	DI19	How did COVID-19 disruption negatively affect coordination among members	
	DI20	How did COVID-19 disruption negatively affect increase custom or taxes	
	DI21	How did COVID-19 disruption negatively affect fluctuation in exchange rates	
Risk Identification	I1	To what extent do these statements apply to your supply chain: we are comprehensively informed about basically possible risks in our supply chain	(El Baz & Ruel, 2020)
	I2	To what extent do these statements apply to your supply chain: we are constantly searching for short-term risks in our supply chain	
	I3	To what extent do these statements apply to your supply chain: in the course of our risk analysis for all suppliers and SC partners, we select relevant observation fields for supply risks	
	I4	To what extent do these statements apply to your supply chain: in the course of our risk analysis for all SC partners, we define early warning indicators	
	I5	Our risk management processes are very professionally designed	
	I5	We carry out a comprehensive and systematic identification of its risks relating to each of its declared aims and objectives.	(Al-Tamimi & Al-Mazrooei. 2007)
	I6	We find it difficult to prioritize its main risks.	
	I7	We have developed and applied procedures for the systematic identification of investment opportunities.	
Risk Assessment	A1	In the course of our risk analysis, we look for the possible sources of supply chain risks.	(El Baz & Ruel, 2020)
	A2	In the course of our risk analysis, we evaluate the probability of supply chain risks.	
	A3	In the course of our risk analysis, we analyze the possible impact of supply chain risks.	
	A4	In the course of our risk analysis, we classify and prioritize our supply chain risks	
	A5	In the course of our risk analysis, we evaluate the urgency of our supply chain risks	
	A6	We assess the likelihood of occurring. risks	(Al-Tamimi & Al-
	A7	We assess risks by using quantitative analysis methods	

	A8	We assess risks by using qualitative analysis methods (.g. high, moderate, low)	Mazrooei. 2007)
	A9	We analyze and evaluate opportunities we have to achieve objectives	
Risk Mitigation	M1	In the course of our risk analysis, we demonstrate possible reaction strategies	(El Baz & Ruel, 2020)
	M2	In the course of our risk analysis, we evaluate the effectiveness of possible reaction strategies	
	M3	Supply chain risk management is an important activity in our company	
Risk Control	C1	Our employees are highly sensitized for the perception of supply risks	(El Baz & Ruel, 2020)
	C2	We have clearly managed to minimize the frequency of occurrence of supply chain risks over the last three years	
	C3	We have clearly managed to minimize the impact of occurrence of supply chain risks over the last three years	
	C4	In our firm monitoring the effectiveness of risk management is an integral part of routine management reporting	(Al-Tamimi & Al-Mazrooei. 2007)
SC Resilience	RE1	To what extent do these statements apply to your supply chain: We are able to cope with changes brought by the supply chain disruption.	(Baz & Ruel, 2020)
	RE2	To what extent do these statements apply to your supply chain: We are able to adapt to the supply chain disruption easily.	
	RE3	To what extent do these statements apply to your supply chain: We are able to provide a quick response to the supply chain disruption.	
	RE4	To what extent do these statements apply to your supply chain: We are able to maintain high situational awareness at all times.	
	RE5	Our company's supply chain is able to adequately respond to unexpected disruptions by quickly restoring its product flow	(Yu et al., 2019)
	RE6	Our company's supply chain can quickly return to its original state after being disrupted	
	RE7	Our company's supply chain can move to a new, more desirable state after being disrupted	
	RE8	Our company's supply chain is well prepared to deal with financial outcomes of supply chain disruptions	
	RE9	Our company's supply chain has the ability to maintain a desired level of control over structure and function at the time of disruption	
	RE10	Our company's supply chain has the ability to extract meaning and useful knowledge from disruptions and unexpected events	
	RE11	Our logistics network is able to adapt to the disruptive situations by quickly re-engineering logistics processes.	(Petit, et al., 2010)
	RE12	Our logistics network is able to promptly and adequately respond to logistics disruptions.	

	RE13	Our logistics network is able to reduce the extent of negative impacts by quick responses.	
	RE14	To what extent do these statements apply to your supply chain: We are able to cope with changes brought by the supply chain disruption.	
SC robustness	RO1	To what extent do these statements apply to your supply chain: for a long time, our supply chain retains the same stable situation as it had before some changes occur	(El Baz & Ruel, 2020)
	RO2	To what extent do these statements apply to your supply chain: When changes occur, our supply chain grants us much time to consider a reasonable reaction	
	RO3	To what extent do these statements apply to your supply chain: Without adaptations being necessary, our supply chain performs well over a wide variety of possible scenarios	
	RO4	To what extent do these statements apply to your supply chain: For a long time, our supply chain is able to carry out its functions despite some damage done to it.	
	RO5	Our organization has documented the measures to be taken when an emergency or disaster occurs, covering crisis communications, business process and it resources recovery	(Hanafy & Shohaıeb, 2017)
	RO6	Our organization has a written disaster recovery plan for systems, data and telecommunications	
	RO7	Our organization has a regular and auditable maintenance schedule for all of the business continuity plan components	
	RO8	Our organization has procedures that ensures speedy resumption of essential operations following system failure/interruption	
	RO9	Our logistics network is able to remain effective and sustain even when internal/external disruptions occur.	(Wieland & Wallenburg, 2012)
	RO10	Our logistics network is able to avoid or minimize risk occurrence by anticipating and preparing for them.	
	RO11	Our logistics network is able to absorb a significant level of negative impacts from recurrent risks.	
	RO12	Our logistics network is able to have sufficient time to consider most effective reactions.	
	RO13	For a long time, our supply chain retains the same stable situation as it had before changed occur	
	RO14	When changes occur, our supply chain grants us much time to consider a reasonable reaction	
	RO15	Without adaptations being necessary, our supply chain performs well over a wide variety of possible scenarios	
	RO16	For a long time, our supply chain is able to carry out its functions despite some damage done to it	(Meepetchdee & Shah, 2007)

Table 0.2: Survey construct items in english

Constructs	Items	Indicator	Reference
SC Disruption Impacts	Considering your experience during COVID-19 pandemic, to what extent have you experienced the impacts on your SC?		
	DI1	COVID-19 disruption negatively affects overall efficiency of our (supply chain) operations.	(El Baz & Ruel, 2020)
	DI2	COVID-19 disruption negatively affects purchasing costs for supply.	
	DI3	Our firm experienced poor logistics performance of logistics service providers during COVID-19.	(Parast, 2020)
	DI4	Our firm experienced fluctuations or shortages on the supply markets during COVID-19.	
	DI5	Our firm experienced unanticipated or very volatile demand during COVID-19.	
	DI6	Our firm experienced unusual customer payment delays during COVID-19.	
	DI7	Our firm experienced drop in delivery speed: Time between order receipt and customer delivery	
	DI8	Our firm experienced drop in market share.	
	DI9	Our firm experienced drop in average selling price (high performance means higher average price).	
	DI10	Our firm experienced changes in the mode of transportation	(Shahbaz et al., 2019)
	DI11	Our firm experienced changes in the packaging and marking details	
	DI12	Our firm experienced changes in the communication ways with the supply chain partners	
Risk Identification	To what extent do the following statements apply to your experiences during the COVID 19 pandemic.		
	I1	Our risk management processes are very professionally designed	(El Baz & Ruel, 2020)
	I2	We are comprehensively informed about basically possible risks in our supply chain	
	I3	We are constantly searching for short-term risks in our supply chain	
	I4	We select relevant observation fields for supply risks	
	I5	We define early warning indicators	
Risk Assessment	To what extent do the following statements apply to your experiences during the COVID 19 pandemic.		
	A1	We evaluate the probability of supply chain risks.	(El Baz & Ruel, 2020)
	A2	We analyze the possible impact of supply chain risks.	
	A3	We classify and prioritize our supply chain risks	

Risk Mitigation	To what extent do the following statements apply to your experiences during the COVID 19 pandemic.		
	M1	We demonstrate possible reaction strategies	(El Baz & Ruel, 2020)
	M2	We evaluate the effectiveness of possible reaction strategies	
	M3	Supply chain risk management is an important activity in our company	
Risk Control	To what extent do the following statements apply to your experiences during the COVID 19 pandemic.		
	C1	We designed appropriate risk responses	(El Baz & Ruel, 2020)
	C2	We have clearly managed to minimize the frequency of occurrence of supply chain risks over the last three years	
	C3	We have clearly managed to minimize the impact of supply chain risks	
SC Resilience	To what extent do the following statements apply to your experiences during the COVID 19 pandemic.		
	RE1	We are able to cope with changes brought by the supply chain disruption.	(El Baz & Ruel, 2020)
	RE2	We are able to adapt to the supply chain disruption easily.	
	RE3	We are able to provide a quick response to the supply chain disruption.	
	RE4	Our company's supply chain can quickly return to its original state after being disrupted	(Yu et al., 2019)
SC robustness	To what extent do the following statements apply to your experiences during the COVID 19 pandemic.		
	RO1	Our supply chain retains the same stable situation as it had before some changes occur	(El Baz & Ruel, 2020)
	RO2	Our supply chain is able to carry out its functions despite some damage done to it.	

Table 0.3: Survey construct items translated in Turkish.

Constructs	Items	Indicator	Reference
SC Disruption Impacts	COVID-19 salgınında yaşadığınız deneyimleri düşünerek, tedarik zinciriniz üzerindeki etkileri ne ölçüde yaşadığınızı belirtiniz?		
	DI1	COVID-19, (tedarik zinciri) operasyonlarımızın genel verimliliğini ne ölçüde olumsuz etkiledi.	(El Baz & Ruel, 2020)
	DI2	COVIV-19, satın alma maliyetlerinizi ne ölçüde olumsuz etkiledi.	
	DI3	COVID-19, sırasında lojistik hizmeti sağlayıcılarınızın performansını ne ölçüde olumsuz etkiledi.	(Parast, 2020)
	DI4	COVID-19 sırasında tedarik pazarlarınızda ne ölçüde kapasite dalgalanmaları veya sıkıntısı yaşadınız.	
	DI5	COVID-19 sırasında beklenmedik vey çok değişken bir taleple karşılaştık.	
	DI6	COVID-19, müşteri ösemelerinizi ne ölçüde olumsuz etkiledi.	
	DI7	CIVID-19, teslimat hızınzı ne ölçüde olumsuz etkiledi? (Sipariş alımı ile müşteri teslimatı arasındaki süre)	
	DI8	COVID-19, Pazar payınızı ne ölçüde olumsuz etkiledi	
	DI9	COVID-19 sırasında ortalama satış fiyatında düşüş yaşadık.	
	DI10	COVID-19 sırasında nakliye modunda değişiklikler yaşadık.	(Shahbaz et al., 2019)
	DI11	COVID-19 sırasında ambalaj ve etiket detaylarında değişiklikler yaşadık.	
	DI12	COVID-19 sırasında tedarik zinciri ortaklarıyla iletişim yöntemlerinde değişiklikler yaşadık.	
Risk Identification	Aşağıdaki ifadeler, COVUD-19 pandemisi sırasındaki deneyimleriniz için ne ölçüde geçerlidir? Lütfen ölçeğe göre belirtiniz:		
	I1	Tedarik zinciri risk yönetimi süreçlerimiz çok profesyonel bir şekilde tasarlanmıştır.	(El Baz & Ruel, 2020)
	I2	Tedarik zincirimizdeki olası riskler hakkında kapsamlı bilgi sahibiyiz.	
	I3	Tedarik zincirimizde sürekli olarak kısa vadeli riskler arıyoruz.	
	I4	Tedarik riskleri tespiti için ilgili gözlem alanlarını seçeriz.	

	I5	Tedarik zincirimizdeki olsı riskler için erken uyarı göstergeleri tanımlıyoruz.	
Risk Assessment	Aşağıdaki ifadeler, COVUD-19 pandemisi sırasındaki deneyimleriniz için ne ölçüde geçerlidir? Lütfen ölçeğe göre belirtiniz:		
	A1	Tedarik zinciri risklerinin olsaılığını değerlendiriyoruz.	(El Baz & Ruel, 2020)
	A2	Tedarik zinciri risklerinin olası etkisini analiz edyoruz.	
	A3	Tedarik zinciri risklerimizi sınıflandırıp önceliklendiriyoruz.	
Risk Mitigation	To what extent do the following statements apply to your experiences during the COVID 19 pandemic.		
	M1	Risk tepki stratejileri uyguluyoruz.	(El Baz & Ruel, 2020)
	M2	Risk tepki stratejilerimizin etkinliğini değerlendiriyoruz.	
	M3	Uygun risk tepkileri tasarlıyoruz.	
Risk Control	Aşağıdaki ifadeler, COVUD-19 pandemisi sırasındaki deneyimleriniz için ne ölçüde geçerlidir? Lütfen ölçeğe göre belirtiniz:		
	C1	Uygun risk tepkileri tasarlıyoruz.	(El Baz & Ruel, 2020)
	C2	Tedarik zinciri risklerinin oluşma sıklığını en aza indirmeyi başardık.	
	C3	Tedarik zinciri risklerinin etkisini en aza indirmeyi başardık.	
SC Resilience	Aşağıdaki ifadeler, COVUD-19 pandemisi sırasındaki deneyimleriniz için ne ölçüde geçerlidir? Lütfen ölçeğe göre belirtiniz:		
	RE1	Teetkilenmesinindarik zincirimizin etkilenmesinin getirdiği değişikliklerle başa çıkabiliyoruz.	(El Baz & Ruel, 2020)
	RE2	Tedarik zincirimizdeki değişikliklere/etkilere kolyaca uyum sağlayabiliyoruz.	
	RE3	Tedarik zincirindeki aksamalara hızlı yanıt verebiliyoruz.	
	RE4	Tedarik zincirimiz yaşanan aksamalardan sonra hızla original durumuna dönebilir.	(Yu et al., 2019)
SC robustness	Aşağıdaki ifadeler, COVUD-19 pandemisi sırasındaki deneyimleriniz için ne ölçüde geçerlidir? Lütfen ölçeğe göre belirtiniz:		
	RO1	Tedarik zincirimiz, bazı değişiklikler meydana gemeden önceki durumu korumaktadır.	(El Baz & Ruel, 2020)
	RO2	Tedarik zincirimiz bazı hasarlara ragmen fonksiyonlarını yerine getirebilmektedir.	

Questionnaire

Supply Chain Risk Management Performance

I am Lama Amir, a student of Master of Engineering Management in Istanbul Kültür University.
I am currently researching "The impact of risk management practices on supply chain performance during COVID-19pandemic" form y thesis with this survey. My questionnaire has 36 questions and require around ten (10) minutes to answer the questions.
This survey is for scientific research purposes, participants will be kept anonymous and the confidentially of your answers are assured.
Your contribution is very valuable and well appreciated. Thanks in advance.

Part A: General Information

1. Size of the company (number of employee): ☐ <10 ☐ 10-49 ☐ 50-199 ☐ 200-500 ☐ >500
2. Experience / age of the company: ☐ <10 ☐ 10-19 ☐ 20-29 ☐ 30-50 ☐ >50
3. Your role in the company (e.g. Sales Manager): ……
4. How long is your experience in the sector? ☐ 5 years or less ☐ 6 to 10 years ☐ 11 years or more
5. How long is your work experience in the current company? ☐ 5 years or less ☐ 6 to 10 years ☐ 11 years or more

Part B: Supply Chain Disruption

Considering your experience during COVID-19 pandemic, to what extent have you experienced the impacts on your Supply Chain?

	(1) "not at all"	(2) "very small extent"	(3) "small extent"	(4) "moderate extent"	(5) "large extent"	(6) "very large extent"	(7) "extremely large (disruptive) extent"
6. COVID-19 disruption negatively affects overall efficiency of our (supply chain) operations.	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
7. COVID-19 disruption negatively affects purchasing costs for supply.	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
8. Our firm experienced poor logistics performance of logistics service providers during COVID-19.	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
9. Our firm experienced fluctuations or shortages on the supply markets during COVID-19.	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
10. Our firm experienced unanticipated or very volatile demand during COVID-19.	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
11. Our firm experienced unusual customer payment delays during COVID_	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
12. Our firm experienced drop in delivery speed: Time between order receipt and customer delivery.	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
13. Our firm experienced drop in market share.	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
14. Our firm experienced drop in average selling price (high performance means higher average price).	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐

Part D: Robustness and Resilience

To what extent do the following statements apply to your experiences during the COVID 19 pandemic. Please specify according to the scale below:

	(1) "Strongly Disagree"	(2) "Disagree"	(3) "Slightly Disagree"	(4) "Neither Disagree nor Agree"	(5) "Slightly Agree"	(6) "Agree"	(7) "Strongly Agree"
29. We are able to cope with changes brought by the supply chain disruption	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
30. We are able to adapt to the supply chain disruption easily.	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
31. We are able to provide a quick response to the supply chain disruption.	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
32. Our company's supply chain can quickly return to its original state after being disrupted	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
33. Our supply chain retains the same stable situation as it had before some changes occur	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
34. Our supply chain is able to carry out its functions despite some damage done to it.	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐

Thank you for your participation.