



MARMARA UNIVERSITY
INSTITUTE FOR GRADUATE STUDIES
IN PURE AND APPLIED SCIENCES



DATA MINING APPROACH IN SUPPLY CHAIN RISK MANAGEMENT

MERVE ER KARA

Ph.D. THESIS

Department of Industrial Engineering

Thesis Supervisor

Prof. Dr. Seniye Ümit OKTAY FIRAT

ISTANBUL, 2017



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Merve ER KARA

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ÖZET

TEDARİK ZİNCİRİ RİSK YÖNETİMİNDE VERİ MADENCİLİĞİ YAKLAŞIMI

Tedarik zinciri riski günümüz dünyasının büyüyen sorunlarından biridir. Tedarik zincirlerindeki tüm stratejik ve operasyonel kararlar risklere ve belirsizliklere maruz kalmaktadır. Tedarik Zinciri Risk Yönetimi (TZRY) sürdürülebilir, rekabetçi ve başarılı işler için ana unsurlardan biridir. Tedarik zincirleri farklı form, olasılık ve etkiye sahip sayısız risk içermektedir. Bu risklerin yönetimi büyük miktarlarda farklı ve dağıtık veri kaynakları ile uğraşmayı gerektirmektedir. Duyarlı ve uyarlanabilir bir TZRY modeli geliştirmek için ana başarı unsuru riskle ilgili verilerin etkili ve verimli kullanılmasıdır. Veri anlamlı bir bilgiye dönüştürülmeden bir şey ifade etmemektedir.

İş zekası ve Veri Madenciliği (VM) iş analitikleri ve başarılı Tedarik Zinciri Yönetimi sistemleri için önemli temel taşlarıdır. Tedarik zincirlerini ve risklerini yönetmede iş zekası ile ilgili sanayi ilgisine rağmen bu alandaki araç ve tekniklerin TZRY'ne adapte edilmesi ile ilgili akademik literatür yeteri kadar zengin değildir. Tezin arka planındaki motivasyon TZRY'nde VM araç ve tekniklerinin uygulanması ile ilgili bir çerçevenin bulunmamasına dayanmaktadır. Bu nedenle bu tez risk yönetiminde daha bilgili ve zeki kararlar verebilmek amacıyla VM-temelli bir TZRY modeli önererek bu araştırma boşluğuna katkıda bulunmayı hedeflemektedir. VM ve TZRY'nin ana adımları tek bir çatıda toplanmıştır. Önerilen yapı VM-temelli bir TZRY sistemi geliştirmek ve risk ile ilgili veriyi analiz etmek amacıyla VM araçlarını ve algoritmalarını uygulamak için kapsamlı bir rehber sağlamaktadır. Bildiğimize göre bu çalışma TZRY alanı için yenidir. Önerilen VM-temelli TZRY yapısı seçilen bir şirkete kısmen adapte edilmiştir. Vaka çalışması için tedarikçiler ile ilgili riskler seçilmiştir. Şirketin ana tedarikçilerini farklı risk çeşitlerine göre kümelemek amacıyla k-ortalamlar kümeleme algoritması uygulanmıştır. Vaka çalışmasının amacı VM-temelli TZRY modelinin uygulanabilirliğini ve avantajlarını gerçek bir endüstriyel çalışma ile göstermektir.

Haziran, 2017

Merve ER KARA

ABSTRACT

DATA MINING APPROACH IN SUPPLY CHAIN RISK MANAGEMENT

Supply chain risk is a growing challenge in today's world. All of the strategic and operational decisions in a supply chain (SC) are exposed to risks and uncertainties. Supply Chain Risk Management (SCRM) is a key element for sustainable, competitive and successful business. Supply chains contain numerous risks with different forms, probabilities and impacts. Management of these risks requires dealing with huge amounts of different and distributed data sources. The key success factor to develop a responsive and adaptive SCRM model is the effective and efficient use of the risk related data. Data means nothing without bringing it to a meaningful knowledge.

Business Intelligence (BI) and Data Mining (DM) are essential cornerstones in business analytics and successful SC management systems. Despite the industrial interest in the use of BI in managing SCs and their risks, the academic literature is not rich enough on the adaption of these tools and techniques in SCRM. The motivation behind this thesis is the lack of a framework to apply DM tools and techniques for SCRM. Therefore, this thesis aims to contribute this research gap by proposing a DM-based SCRM model in order to make more informed and intelligent decisions in risk management. The main steps of DM and SCRM are combined in a unique framework. The proposed framework provides a comprehensive guide to develop a DM-based SCRM system and apply DM tools and algorithms for analyzing risk related data. To the best of our knowledge, this study is novel in SCRM area. The proposed DM-based SCRM framework is partially adapted to a selected enterprise. Supplier related risks are selected for the case study. K-means clustering algorithm is applied to cluster core suppliers of the company based on different risk types. The aim of the case study is to represent the applicability and advantages of the DM-based SCRM model with a real industrial study.

June, 2017

Merve ER KARA

CLAIM FOR ORIGINALITY

DATA MINING APPROACH IN SUPPLY CHAIN RISK MANAGEMENT

Risk is an important issue that threaten the sustainability of supply chains. The key success factor to develop a responsive and adaptive Supply Chain Risk Management system is the effective and efficient use of the risk related data. There is a need for researches on how to systematically analyze risk related data to discover and assess risks. A limited number of researchers studied on the use Data Mining techniques in Supply Chain Risk Management. This thesis aims to contribute this research gap by proposing a Data Mining based Supply Chain Risk Management model to make more informed and intelligent decisions in risk management. The strength and originality of this thesis comes from the fact that a holistic approach is proposed by integrating the main steps of Data Mining and Risk Management. This study is novel in the supply chain area.

The proposed Data Mining based Supply Chain Risk Management framework is partially adapted to a selected company. A case study is performed to cluster suppliers based on their risk profile. The weights of the supplier evaluation criteria are identified by the Best-Worst method. Then k-means clustering algorithm is applied on the weighted supplier risk data. This is the first study that applies cluster analysis to group suppliers based on their risk profile and the first study that uses Best-Worst method and cluster analysis together.

The results of the Data Mining algorithms provide new insights for supply chain risk management actions. This thesis will provide an initial basis for further researches and developments in the application of Data Mining algorithms in risk management.

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SYMBOLS

a_{Bj}	: The preference of the best criterion over criterion j
a_{jw}	: The preference of the criterion j over the worst criterion
c_i	: Criterion i
ε	: Objective function value of the Best-Worst Method problem
S_i	: Supplier i
w_i	: Weight of criterion i
w_i^*	: Optimal weight of criterion i



ABBREVIATIONS

AHP	: Analytical Hierarchy Process
ANP	: Analytic Network Process
BI	: Business Intelligence
BWM	: Best-Worst Method
DEA	: Data Envelopment Analysis
DM	: Data Mining
DSS	: Decision Support System
ERM	: Enterprise Risk Management
ETL	: Extract, Transform and Load
FMEA	: Failure Mode and Effect Analysis
FMECA	: Failure Mode, Effects and Criticality Analysis
IT	: Information Technology
KDD	: Knowledge Discovery in Databases
KPI	: Key Performance Indicator
KMO	: Kaiser-Meyer-Olkin
MCDM	: Multi-Criteria Decision-Making
NN	: Neural Network
PCA	: Principle Component Analysis
RDW	: Risk Data Warehouse
RI	: Risk Intelligence
OLAP	: Online Analytical Process
RPN	: Risk Priority Number
SC	: Supply Chain
SCM	: Supply Chain Management
SCDM	: Supply Chain Disruption Management
SCRM	: Supply Chain Risk Management
SSCM	: Sustainable Supply Chain Management
TOPSIS	: Technique for Order Performance by Similarity to Ideal Solution

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1. INTRODUCTION

Supply chain (SC) networks are complex, interconnected, geographically dispersed and dynamic networks. There are a lot of factors that affect the performance of SCs such as quality issues, agility, transportation capability, technology level, interconnections, and risks. All of the strategic and operational decisions in a SC are exposed to risks and uncertainties. Uncertainty about the future causes risks (Waters, 2011). Risk is an important issue that threaten the sustainability of SCs. SC risk can be defined as the probability of occurrence of a failure, harm, damage or loss from unforeseen events (Zsidisin and Ritchie, 2009; Waters, 2011). SC risk is a growing challenge in today's world. Companies should manage risk as well as performance and efficiency for sustainability and competitiveness.

SC risks can result from a wide variety of sources including demand and supply variability, poor performing suppliers, price fluctuations, dynamic consumer markets, global economic uncertainty, transportation of dangerous products and even unexpected events such as work accidents, cyber-attacks, natural disasters and terrorism (Er Kara and Oktay Firat, 2016). While some of the SC risks are out of the control of organizations, most of the major risks are controllable/influencable to some degree (PwC&MIT Forum, 2013). The triggering factors of SC risks, their relationship and possible consequences are very complex. The effects of a possible disruptive event may propagate quickly to the entire SC. The losses resulting from SC risks may be classified under six main headings: financial, performance, physical, psychological, social and time losses (Brenchley, 2000; Harland et al., 2003). SC disruptions generally disrupt business operations, cause loss of revenue, sales and customers, and damage corporate image (Er Kara, Oktay Firat, 2015). However, some risk events may result in severe consequences such as human death or damages on buildings and infrastructure, etc. (Bradley, 2014). A disruptive event affecting a process or a member of a SC may damage the other operations in the current company or other members of the SC. Furthermore, if low-impact disruptions occur simultaneously or create snowball effect, they may cause to serious consequences (Vilko and Hallikas, 2012).

Decision making is getting harder every day due to increasing uncertainty, complexity, dynamism and competitiveness in the global business environment. There are various business trends and developments that rise the risk exposure levels of SCs and make companies vulnerable to unforeseen disruptions. Some of these developments can be listed as follows: globalization of business and markets, increasing quality and service levels, reduced product lifecycles, rising use of outsourcing, increased collaboration and relationships with SC partners, and development of information and communication technologies (Norrman and Jansson, 2004; Lavastre et al., 2012; Thun and Hoenig, 2011). In recent years, Supply Chain Management (SCM) focus on more proactive, systematic, strategic, sustainable, corporate and customer-focused approaches by using leaner, more flexible, agile, robust and competitive strategies (Zsidisin and Ritchie, 2009). Although these developments have reduced the total SC costs, they increase the vulnerability of companies to unforeseen disruptions and cause companies to lose their adequacy to absorb these disruptions (Tuncel and Alpan, 2010). There is a need for new and effective approaches to cope with the increasing risk exposure levels and manage growing information load.

In today's competitive global environment, Supply Chain Risk Management (SCRM) is a key element for sustainable and successful business. SCRM is the implementation of strategies, models, tools and techniques to identify, evaluate, manage and monitor SC risks for reducing vulnerability and ensuring the sustainability of the SC (Jüttner, 2005; SCRLC, 2011; Khan and Zsidisin, 2012). This emerging field may be seen as the intersection of SCM and Enterprise Risk Management (ERM). The aim of SCRM is to understand and manage the risks and their effects, and try to take proactive and preventive actions for risks. Understanding risks is the first step to build a resilient and sustainable SC, and develop proactive risk management strategies (Er Kara and Oktay Fırat, 2016). Most of the literature in SCRM area focus on identifying risks and their sources; quantitative analysis in the SCRM field are relatively lacking (Giannakis and Louis, 2011; Tuncel and Alpan, 2010).

SCRM gained attention in the late 1990s as a result of some major risk events (Takata and Yamanaka, 2013; Er Kara and Oktay Fırat, 2015). Risk events highlight the importance of early detection, preparedness and response to risks. Risk management within SCs is one of the vital issues for every organization in a SC. SCRM concept is

capturing increasing interest by many researchers and executives due to rapidly changing global markets and increasing complexity of SCs. However, the number of researches/thesis on SCRM is very limited in Turkey (Güven, 2010; Bahar, 2007; Haksöz, 2013).

SCs contain numerous risks with different forms, probabilities and impacts. Management of these risks requires dealing with huge amounts of different and distributed data sources (Marra et al., 2012; Lam and Quinn, 2014). Increased globalization, collaboration, communication and the developments in information technologies lead to high information loads in SCs. Terabytes of data are generated and transmitted in everyday operations in many SCs; e.g. production records, billing records, delivery records, surveys, etc. The key success factor to develop a responsive and adaptive SCRM is the effective and efficient use/analysis of the risk related data. Due to modern information technology, there are cheap and efficient methods to collect, store, retrieve, transfer and analyze data today (Ranjan and Bhatnagar, 2011). Scope and volume of the SC data are growing with the increasing complexity of the SC networks and advances in technological developments. However, data means nothing without bringing it to a meaningful knowledge. The role of knowledge in SCRM gained increasing attention with the impact of the fourth industry revolution that can be defined as digital transformation.

Today many companies use Business Intelligence (BI) and Data Mining (DM) tools and techniques in SCM to make efficient and timely decisions (Manhattan Associates, 2008). In addition, the number of companies that use BI tools to support SCRM process is increasing. However, the academic literature is not rich enough on the use of BI for managing the risks in SCs, and there is a research gap for the relationship between these two areas (Petrini and Pozzebon, 2009; Lee and Kulkarni, 2011; Wu et al., 2014). There are only a few studies in the literature related with the application of DM algorithms in SCRM (Thun and Hoenig, 2011; Ye et al., 2012; Le et al., 2013). This field is new and promising for providing effective risk management systems. There is a need for researches on how to systematically analyze risk related data to discover and assess risks (He and Song, 2009). The motivation behind this thesis is the lack of a framework to apply DM tools and techniques for SCRM in the academic literature. Therefore, this thesis aims to contribute this research gap by proposing a DM-based SCRM model in

order to make more informed and intelligent decisions in risk management. DM tools and algorithms have the potential to bring new insights to SCRM area.

DM is featured by Information Technologies to extract hidden and useful knowledge in large and separate databases (Ranjan and Bhatnagar, 2011). DM is one of the core technologies for today's business life. The application of DM tools and techniques is increasingly growing in all areas of business life. The main steps of DM and SCRM are combined in a unique framework in this thesis. To the best of our knowledge, this study is novel in the SCRM area. DM can be used in the discovery, assessment, analysis, prediction, monitoring and prevention of the risks in SC networks. DM helps companies to discover risks and opportunities easily and improves visibility of risks. In the proposed model, DM is used to discover useful information about risks for identifying effective risk management actions.

The primary goal of this thesis is to develop a DM-based SCRM model in order to increase the effectiveness of risk management decisions by utilizing the results of DM algorithms. The proposed framework provides a comprehensive guide to apply DM tools and algorithms for analyzing risk related data and develop successful DM-based applications in SCRM. To our knowledge, there is not such a framework in the literature. The proposed DM-based SCRM framework is partially adapted to a selected enterprise. Supplier related risks are selected for the case study. Cluster analysis is proposed as an explanatory approach to group suppliers based on their risk profile. Suppliers are assessed based on seventeen qualitative and quantitative criteria related with different risk types. The weights of the risk criteria are identified by the Best-Worst Method (BWM), which is a new multi-criteria decision making method (Rezaei et al., 2015). Four factors are extracted from these seventeen risk criteria by applying Factor Analysis. Then k-means clustering algorithm is applied to group suppliers based on their risk attributes and three clusters are created with different risk exposure levels. To the best of our knowledge, this is the first study that applies cluster analysis to group suppliers based on their risk profile and the first study that uses BWM and cluster analysis together. The results of the clustering algorithm is used in order to examine the risk characteristics of the suppliers in different clusters and investigate the relationships between different risk factors. The interpretation of the DM results provides insights for risk management actions to mitigate supplier risk. Suppliers with a high-risk profile can

be eliminated or supplier development programs can be developed based on the results of the analysis. The aim of the case study is to represent the applicability and advantages of the DM-based SCRM model with a real industrial study.

Chapter 2 gives the research methodology and outline of the thesis. Chapter 3 focuses on the definition and categorization of SC risks, oft-cited risk events, SCRM steps and methods used in mitigating SC risks. Chapter 4 explains BI and DM concepts, the role of BI in managing SCs and their risks, and the risk indicators used to measure and track SC risks. Then risk criteria and clustering approaches used in supplier evaluation and selection process are given. Chapter 5 introduces the proposed DM-based SCRM model. Potential application areas of DM in SCRM are also discussed. Chapter 6 explains the adaption of the proposed model to a selected enterprise and introduces the case study that aims to cluster the core suppliers of the company considering different risk factors.

This thesis will provide an initial basis for further researches and developments in the application of DM algorithms in SCRM. The proposed DM structure will support and enhance the SCRM processes (such as risk identification, risk assessment, risk management actions and risk monitoring), support SC intelligence and help companies to survive and compete within today's complex and dynamic business environment. The results gained by the DM algorithms will provide a realistic picture of the state of the SC risks for decision makers seeking to manage risks in SCs.

2. RESEARCH METHODOLOGY AND OUTLINE OF THE THESIS

This chapter presents the research questions, objectives, and methodology, and explains the outline of the thesis. Research methodology literature is reviewed to guide the development of the thesis in the following steps; work plan, literature review, data collection, and selection of the qualitative and quantitative research methods (Silverman, 2005; Wilson, 2010; Myers, 2013). The idea behind the thesis is to explore the use of DM in SCRM and develop a general DM-based structure for SCRM. This thesis integrates two different research fields, hence it contains a wide range of literature review. The flowchart/outline of the thesis is represented in Figure 2.1 in order to clearly depict the main parts and flow of the study. During reviewing the SCRM literature, a research gap is discovered for the use of DM tools and techniques and thus this thesis has started with an idea to utilize from DM in this area.

The objective is to investigate the potential and power of DM algorithms in SCRM area. Accordingly, the basis of the thesis depends on the following research questions:

- i) How can DM enhance the SCRM process?
- ii) How and in which steps can DM algorithms be used in SCRM?
- iii) Which technique can be used in which risk area?
- iv) What are the benefits of DM in SCRM?

Before development of a general DM-based SCRM model, a comprehensive and multi-dimensional literature review has been done. The literature review may be divided into four main parts: i) SC risks, ii) main steps and approaches in SCRM, iii) BI and DM, and iv) the applications of BI and DM tools in SCRM. These literature reviews provide the background information for the incorporation of SCRM and DM area.

The research goal is to develop a DM-based SCRM framework by integrating the main steps of DM and SCRM. A comprehensive DM-based SCRM model is developed by utilizing from relevant literature and discussions with both SC risk and BI experts. The model consist of various steps that can be used as a guideline to assist SC executives

and practitioners to develop a DM-based risk management structure. All of the steps are explained in detail. Theoretical background of the model is based on the related literature and face-to-face interviews with SC and BI experts from business life.

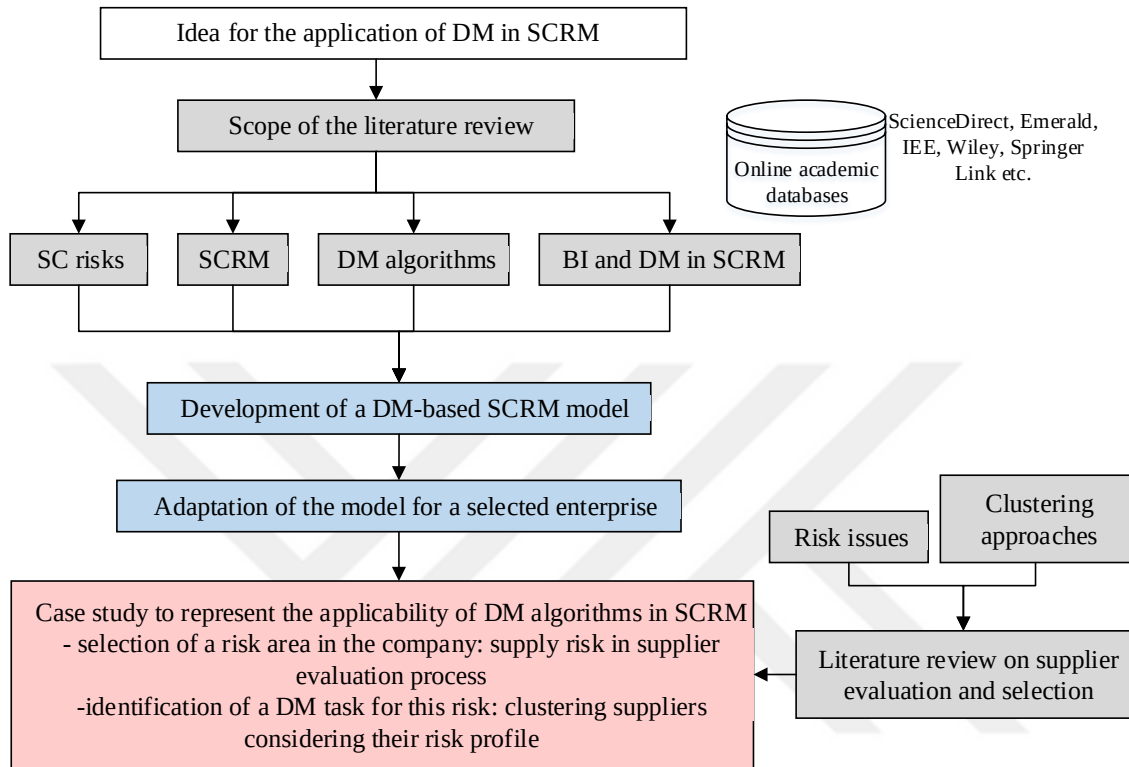


Figure 2.1. Outline of the thesis

Some of the parts of the study requires technical expertise including the development of a data warehouse, its use in the proposed model and determination of the required hardware for the model. Hence, face-to-face interviews are conducted with two specialists. One of them is a technical adviser in the IT department of an insurance company (Doruk, 2017). The other one is a consultant in one of the most important information technology providers in the world (Pamuk, 2017).

The proposed DM-based structure will support and enhance the SCRM processes (e.g. risk identification, risk assessment, risk management actions and risk monitoring), support SC and risk intelligence and help companies to survive and compete within today's competitive and dynamic business environment. Proactive and preventive risk management strategies are inadequate in SCRM area. The results gained by the DM algorithms will provide a realistic picture of the state of the SC risks for decision

makers seeking to manage risks in SCs. This thesis will provide an initial basis for further researches and developments in the application of DM algorithms in SCRM.

The steps of the proposed DM-based framework are partially adapted to a selected company in order to represent the applicability of the model. First a risk management team is created that contains risk experts, domain experts and a data analysis expert. The risks that the company is exposed to are identified and explained with discussions, brainstorming and focus group studies. A survey is also performed in order to assess some of the most important risk factors. Then, the risk indicators that may be used to measure and track these risks are identified with discussions and literature review. These indicators are determined in order to provide an initial basis of a risk data warehouse for the company.

Potential application areas of DM in SCRM are discussed. A case study research approach is performed in order to demonstrate the efficiency of the proposed framework. It is not possible to apply the model for all risk types and all DM tasks. Therefore, as in parallel to the steps of the model, first a specific risk area is identified by using the results of a survey applied to the staff and discussions with the managers in the company. One of the most critical processes in the company is the supply of the parts required to produce mills. Hence, the risk management team decided to analyze the risk data associated with supplier related risks. Clustering of suppliers is selected by using the guide questions for the determination of the DM application in the proposed model. Suppliers are evaluated according to different qualitative and quantitative risk factors. Two different areas of literature are also reviewed for this part of the study: i) Literature review on the risk criteria in supplier evaluation and selection, and ii) Clustering approaches in supplier evaluation and selection. Risk evaluation criteria are assessed by three decision makers via using the BWM that is proposed by Rezaei (2015). Suppliers are clustered according to their risk profile for different risk types. K-means algorithm is selected to group suppliers based on different risk types and three supplier clusters are created with different risk levels. The analysis is performed by using SPSS 20. The results of cluster analysis are interpreted with the domain experts in the company. Post-hoc analysis are performed.

Table 2.1 summarizes the research design of the thesis based on the decision step, research methods that are used in this step, and aim of these methods.

Table 2.1. Summary of the research design

Decision step	Methods	Aim
Building a theoretical model	• Literature review • Face-to-face interviews with SC and BI experts	Development of a DM-based SCRM model that will act as a guideline for the implementation of DM tools and techniques in SCRM
Application of the model to a real world problem	• Observation • Interviews • Survey • Focus group study • Brainstorming • Case study (clustering)	Partially adapting the proposed model to a selected company (includes various steps such as identification of risks, choosing the risk indicators, assessment of risks, etc.)
Data collection for clustering	• Gathering data from operational databases • Supplier evaluation survey	Collection of both quantitative and qualitative supplier risk data
Exploratory data analysis	• Best-worst method to weight supplier risk criteria • K-means clustering algorithm	Clustering suppliers based on their risk profile

3. SUPPLY CHAIN AND RISK MANAGEMENT

This chapter focuses on SC risks and methods that are used to manage these risks. First, a brief introduction is presented in order to understand risk and uncertainty concepts in SCs and the developments that trigger the occurrences of SC risks. Some of the oft-cited risk events are discussed in order to enhance the understanding on the origins of SCRM. Then a comprehensive review on SC risks is given and a new categorization for SC risks is proposed. After that, the main steps and methods used in SCRM are explained. Finally, the relationship between sustainability and SCRM concepts is introduced briefly.

3.1. Risks and Uncertainties in Supply Chains

SC is the entire network of organizations including suppliers, manufacturers, retailers, distributors, stores, logistics providers, service providers and customers that participate in the manufacturing, delivery and sale of a particular product or a service (Sodhi and Tang 2012). SCM, which is originally introduced in the early 1980s, is the process of planning, integrating and controlling the operations within a SC with the aim of maximizing the value and gaining competitive advantage (Sinha, 2009; Mangan et al., 2012). SCM includes coordination of materials/products, information, services and finance flows between the partners of the SC. It covers the movement, processing and storage of raw materials and finished goods from supply to consumption (Heidarzade et al., 2016). SCM helps to increase the productivity and profitability of organizations (Gunasekaran et al., 2004).

There are many strategic and operational decisions in a SC. Supply chain risk is a strategic issue that should be considered in the decision making processes of organizations (e.g. product storage, delivery and marketing decisions). Some past risk events highlighted the weaknesses of SCs for disruptions. Risk is an ambiguous term and there is not a certain definition of SC risk. The origin of the word “risk” can be either the Arabic word “risq” or the Latin word “riscum” (Merna and Al-Thani, 2011). Both of them have connotation of a fortuitous and favorable event. Risk is defined as the effect of uncertainty on objectives in ISO 31000 Risk management principles and guidelines (2009). March and Shapira (1987) described risk with a classical decision

theory perspective as follows: *“reflecting variation in the distribution of possible outcomes, their likelihoods, and their subjective values”*. The usage of the term changes according to the region, time, culture and area.

“Risk” term has been used for centuries in a lot of areas, but it is a recent and growing subject in SCM. SC risk can be defined as the potential (or probability of) occurrence of a failure, harm, damage or loss from unforeseen events (Zsidisin and Ritchie, 2009; Waters, 2011). The advances in the computer science and information technologies, and the global nature of the supply chains make them vulnerable to a range of risks and bring unforeseen problems. Companies can develop effective risk reduction strategies by understanding different kinds of risks and their relationship. SC risks can result from a wide variety of sources including demand and supply variability, poor performing suppliers, price fluctuations, dynamic consumer markets, global economic uncertainty, transportation of dangerous products and even unexpected events such as work accidents, faults in information systems, natural disasters and terrorism. Risks can emanate both within and outside the organization. While some of the SC risks are out of the control of organizations, most of the risks are controllable/influencable (PwC&MIT Forum, 2013). Cavinato (2004) divided SCs into five sub-chains to identify risks: physical, financial, informational, relational and innovational. Gaonkar and Viswanadham (2004) defined three forms of SC risks; deviation of one or more parameters from expected values, disruption due to non-availability of the components or activities of SC, and unforeseen catastrophic disruptions (disasters).

Supply chains contain uncertainties and thus risks inherently. Uncertainty about the future causes risks (Waters, 2011). While uncertainties are genuinely unknown, risks that are outcomes of uncertainties can be measured (Norrman and Jansson, 2004). Different terms have been used synonymously instead of risk; uncertainty, disruption, vulnerability, disturbance, disaster, hazard, or crisis (Ghadge et al., 2012; Heckmann et al., 2015). There are various vague definitions of risks. Table 3.1 gives the definitions of some concepts related to SC risk to create an understanding about the differences of these terms.

Table 3.1. Existing definitions of some terms related with supply chain risk

Term/Concept	Definition	Reference
Supply Chain Risk	<i>"potential loss for a supply chain in terms of its target values of efficiency and effectiveness evoked by uncertain developments of supply chain characteristics whose changes were caused by the occurrence of triggering-events"</i>	Heckmann et al. (2015)
Supply Chain Vulnerability	<i>"the concept used to describe the extent to which a supply chain is susceptible to a specific or unspecific risk event"</i>	Heckmann et al. (2015)
Resilience	<i>"the ability of a system to return to its original state or move to a new, more desirable state after being disturbed"</i>	Christopher and Peck (2004)
Firm's resilience to supply chain disruptions	<i>"the capability of the firm to be alert to, adapt to, and quickly respond to changes brought by a supply chain disruption"</i>	Ambulkar et al., 2015

According to Khan and Zsidisin (2012) risk contains both the possibility of loss and gain. Risks are not generated by only threats; potential opportunities can increase unsystematic risks for the organizations too (Brindley and Ritchie, 2004). Therefore, enterprises should effectively balance the risks and potential opportunities for an efficient risk management. Companies should also consider the relations between different types of risks. Risk elements are not distinct between each other; most of them are interrelated. Furthermore, with technological developments and the changes in SC structures, new and additional sources of uncertainties and risks are emerging every day.

Heckmann et al. (2015) made an extensive literature analysis on risk concept and SC risk approaches. Some of the notes from their study are listed in the following:

- The relation between probability theory and risk started to be seen since the 1950s and has been applied in many studies.
- Only a few authors have explicitly defined SC risk.
- While most authors categorize SC risk related to the triggering events/sources, some approaches relate risk to its consequences.

- Most of the authors describe SC risk as the deviation of the affected objective usually in terms of profit and cost, but minor studies regard risk as supplier failures and customers' satisfaction.
- SC resilience is defined either as the ability to reduce SC risk or to deal with SC vulnerability.
- Risk is determined by the risk attitude of the decision maker: risk-averse, risk-seeking and risk-neutral.

Heckmann et al. (2015) also identified the core characteristics of risk as shown in Figure 3.1.

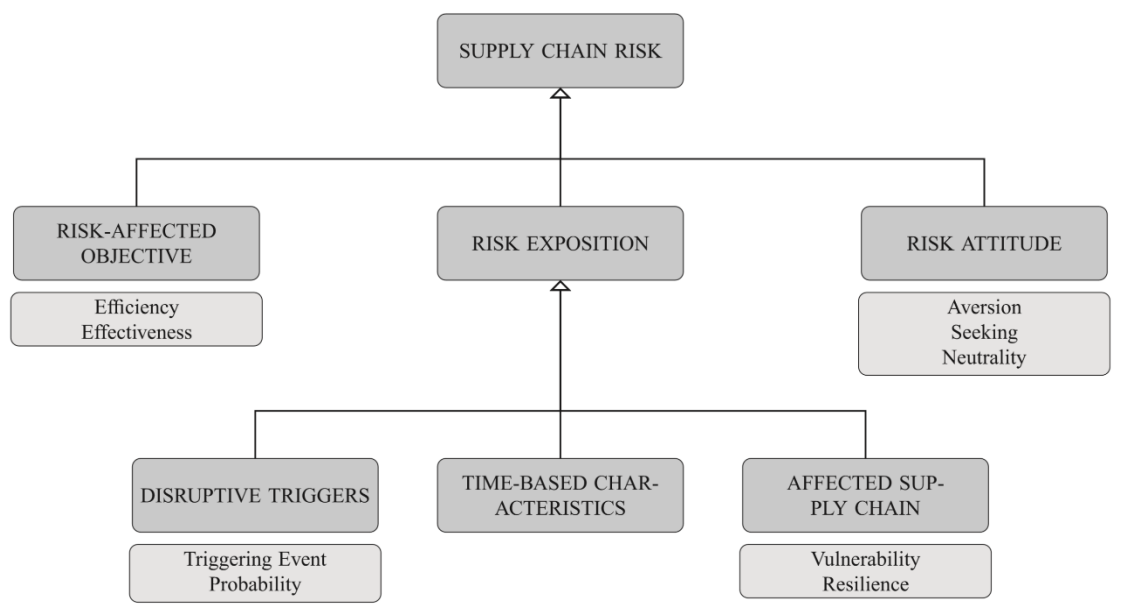


Figure 3.1. Core Characteristics of Supply Chain Risk (Heckmann et al., 2015)

SC risks include the circumstances that disrupt normal business operations within the SC. SC disruptions can cause high costs, loss of customers or reputation, and decreased revenues. SC risks can cause the following disruptions (Sawik, 2013; Bradley, 2014; Lavastre et al., 2012; Takata and Yamanaka, 2013; Thun and Hoenig, 2011; Wu et al., 2013; Lee and Kulkarni, 2011);

- Interrupt the flow of goods/materials/products/services and information through the SC,
- Disturb SC operations,
- Cause delays for customers,

- iv) Cause economic losses / Cause loss of revenue,
- v) Can have high negative effects on the performance of the firms and the SC,
- vi) Increase the cost of operations,
- vii) Level buildings and destroy infrastructure,
- viii) Disrupt production schedules,
- ix) Cause customer dissatisfaction and/or loss of customers,
- x) Cause loss of sales,
- xi) Cause negative effects on corporate brand/image or a bad reputation,
- xii) Decline in market share,
- xiii) Regulatory penalties,
- xiv) Cause damages in security and health.

The losses that may be caused by risks can be categorized as follows (Brenchley, 2000; Harland et al., 2003): financial, performance, physical, psychological, social and time losses. Potential risk factors must be analyzed carefully for the continuity of the organization. The criticality of a risk event is generally measured by the probability and the impact of this disruptive event. These are estimated by using the current data, observations or expert opinion. Another measure for risk is the likelihood of an event being detected before or after its occurrence (Bradley, 2014). There are different forms and attributes of risks. These properties may vary due to the SC operations (Xia and Chen, 2011). Risk attributes include the source of the risk, probability, impact, time and location (Kayis and Karningsih, 2012).

There are various business trends and developments that trigger the occurrences of risks in SCs. Some of them can be listed as follows (Norrman and Jansson, 2004; Lavastre et al., 2012; Norrman and Jansson, 2004; Thun and Hoenig, 2011);

- Growing sizes of SCs,
- Increased complexity and interconnections in SCs,
- Increased competitiveness among the companies,
- Globalization of SCs/business and markets,
- Geographically dispersed SCs,
- Reduction of supplier base,
- More intertwined and integrated processes between companies,

- Reduced/shorter product life cycles,
- Reduced buffers,
- Shorter lead times,
- Reduced time-to-market,
- Increased quality and customer service levels,
- Increased complexity of products,
- Increased demand for on-time deliveries,
- Lean, agile and customer-focused strategies to reduce costs and increase quality, speed, efficiency, and flexibility,
- Increases in outsourcing and off-shoring,
- Development of information and communication technologies and growing information load.

These recent developments change the nature and complexity of SCs, bear the risk of making companies more vulnerable to unforeseen disruptions and cause companies to lose their adequacy to absorb disruptions. Some of the recent trends and their risk impacts are determined according to expert group findings in World Economic Forum (World Economic Forum Report, 2012). These trends are globalization, specialization, complexity, lean processes, information availability and government legislation. Xia and Chen (2011) gave some examples to the factors increasing the complexity of a SC risk system; i) too many suppliers, ii) cross-production processes, iii) a long logistics cycle, and iv) expanded product catalogues.

3.2. Oft-cited Supply Chain Risk Events in the Literature

SCRM gained attention in the late 1990s as a result of the occurrences of big SC risk events (Takata and Yamanaka, 2013). Past real-world SC disruptions are important in order to provide an understanding on the evolution of SCRM. These events negatively affected various companies in different countries and have been debated in industrial sectors very much. Er Kara and Oktay Firat (2015) made a comprehensive review on the major and oft-cited SC disruptions in the literature.

Table 3.2 provides a review on some major SC disruption events that are oft-cited in the SC risk literature.

Table 3.2. Some of the oft-cited risk events in the literature

Risk Event	Year	Results	Reference
Fire in Aisin Seiki's main factory	1997	Toyota shut down 18 plants for almost two weeks & Estimated cost of the disruption was \$195 million and sales loss was 70,000 vehicles	Fang et al., 2013; Norrman and Jansson, 2004
Taiwan earthquake	1999	Created huge losses for many electronics companies supplied with the components by Taiwanese- supply shortage	Bradley, 2014; Sawik, 2013; Basole and Bellamy, 2014
Philips wafer fabrication operation fire in New Mexico	2000	Caused Ericsson an estimated loss of \$400 million and arguably a much weakened position in the cell phone market	Takata and Yamanaka, 2013; Sawik, 2013; Heckmann et al., 2015; Tang and Musa, 2011
Typhoon that disrupted suppliers in South East Asia	2001	Disrupted air transport in South-East Asian region	Lavastre et al., 2012
Terrorist attacks of September 11, 2001	2001	Ford and Toyota had to stop their production in their manufacturing plants in the US due to significant delays in delivery of parts coming from foreign countries	Thun and Hoenig, 2011; Basole and Bellamy, 2014
Excess inventory of Cisco Systems Inc.	2001	Cisco Systems Inc. wrote off \$2.25 billion excess inventory	Lai et al., 2009; Norrman and Jansson, 2004
Inaccurate supply planning of Nike	2001	Caused inventory shortage of footwear models and the sales for Q3 2001 were \$100 million of target	Norrman and Jansson, 2004
Disease	2001	Luxury car manufacturers like Volvo and Jaguar had to stop deliveries due to lack of quality leather supply	Norrman and Jansson, 2004
Hurricane Katrina	2005	Wal-Mart performed well and recovered quickly	Bradley, 2014; Fang et al., 2013; Heckmann et al., 2015
Defective high pressure pumps for diesel fuel injection systems	2005	Caused millions of dollars damage to Robert Bosch (entire SC was affected)	Thun and Hoenig, 2011
Bankruptcy of the Chrysler's supplier, Plastech	2008	Led to the temporary shutting down of four Chrysler plants in 2008 that resulted in Chrysler losing millions of dollars	Trkman and McCormak, 2009
The closure of the European airspace	2010	The closure of the European airspace	Fang et al., 2013; Heckmann et al., 2015
High volatility of euro and possible appreciation of the Chinese yuan	2010	Have posed significant risks to many companies involved in offshore outsourcing and global trades	Liu and Nagurney, 2011
Floods in Thailand	2011	Associated supply shortages reduced Toyota's production	Tomlin, 2014; Sawik, 2013; Heckmann et al., 2015

One of the major most-cited events is the Philips wafer fabrication operation fire in New Mexico in 2000 (Tang and Musa, 2011; Basole and Bellamy, 2014; Norrman and Jansson, 2004). Since Ericsson used a single-source policy, a fire in its chips' supplier caused Ericsson an estimated \$400 million loss and disrupted its position in the cell phone market (Tang and Musa, 2011). Norrman and Jansson (2004) described Ericsson's new approach to SCRM after this accident in its sub-supplier and gave some examples to SC risks and their rippling effects.

Imbalance of supply and demand is one of the most common problems of companies (Tomlin, 2014). Supply-demand imbalance may result from various factors including failures in the supply of raw materials and parts, wrong forecasts and changes in the market etc. (Er Kara and Oktay Firat, 2015). In 1997, the suppliers of the Boeing Aircraft Company did not believe the demand forecasts of the company and produced less than needed. This event caused the company to lose billions of dollars due to shortage of raw materials and semi-finished goods (Özbay, 2008). In 2003, during Christmas, Motorola and Sony Ericsson faced problems in the supply of critical parts required in the production of screens, microchips and cameras (Vesa, 2005).

Today many companies collaborate with other companies to increase their service levels and share their risks in various functions such as logistics, IT system, after sales service, etc. (Er Kara and Oktay Firat, 2015). As an example, Cisco Systems company work with a software vendor, MCA Solutions, in order to apply an enhanced service planning software (Cohen, 2004). Cisco systems increased its service performance and profitability, and decreased risks by outsourcing software development. Tellabs company agreed with DHL Logistics for transportation and warehousing activities with the aim of increasing their service level (Cohen, 2004).

A disruptive event affecting a process or a member of a SC may damage the other operations in the current company or other members of the SC. Furthermore, if low-impact disruptions occur simultaneously or create snowball effect, they may cause to serious consequences (Vilko and Hallikas, 2012). Taiwan earthquake caused delayed shipments of key computer components in many electronic firms such as Compaq and Apple (Basole and Bellamy, 2014).

An efficient SCM requires coordination and collaboration between SC stakeholders. Information sharing between SC members increase the visibility of the SC and hence decrease risk exposure levels. Dell Computer Company is one of the best examples to an efficient coordination with suppliers. The main factors that drive the company to success can be listed as follows (Hill and Jones, 2012): i) Efficient demand forecasts by analyzing demand patterns, customer satisfaction levels, and changes in the requirements and preference of customers; ii) Decreasing costs by using web-based information systems to coordinate with customers and suppliers; iii) Fast response rate to potential disruptions as a result of real-time data processing about their products; iv) Sharing real-time sales data with suppliers. SC visibility provided by Dell helps the company to respond to changes and risk events (e.g. demand volatility and customer complaints) immediately.

Technological developments, ERP software and web-based communication tools enhance the efficiency and success of SCM practices. However, these technological developments also bring new risks such knowledge leakage, customer data theft, cyber-attacks, viruses, etc. (Boyson, 2014; Er Kara and Oktay Fırat, 2015). According to the Risk Barometer report of Allianz (2015), cyber risk has the most increase among other risks.

Companies have to track the changes in their industry and market in order to identify potential threats and new opportunities. New competitors entering the market is one of the most common risks in this area. New competitors may lead to loss of market share and decreases in profits. As an example, cable television companies have started to offer telephone service with the same cables that deliver television programs (Hill and Jones, 2012). This technological development turned these companies to competitors of telephone companies.

There are also some rare and catastrophic risks such as natural disasters, fire, war, terrorism, etc. (Er Kara and Oktay Fırat, 2015). In 2005, Katrina and Rita hurricanes disrupted petrol and natural gas operations and caused the stoppage of the 28% of total energy production (Carbaugh, 2014). Terrorist attacks of September 11 2001 in the United States affected some firms indirectly, and Ford and Toyota stopped their manufacturing in the United States due to supply disruptions (Thun and Hoenig, 2011).

Past risk events highlight the importance of the early detection, preparedness to disruption and quick response to risks. Bradley (2014) gave the West Coast dock strike in 2002 as an example to a detectable event. Since dock strikes happen when labor-management contracts are negotiated, a company that observes the signals during negotiations can predict the likelihood of a strike. The likelihood of some extreme weather events can be estimated too (e.g. heavy snowstorms in the Alps in winter) (Trkman and McCormack, 2009).

The aforementioned events caused the SC practitioners to investigate SC risk issues in a greater depth and triggered the development of the SCRM. Also everyday problems such as failure of equipment or quality problems increase the attention on this issue too. Companies focus on SC resiliency to take precautions and respond to such disruptive events.

3.3. A Review of Supply Chain Risk Literature and a New Categorization for Risks

This section includes the literature review on SC risks and a new comprehensive categorization for SC risks.

3.3.1. An Overview of Literature Survey

Supply chains contain various types of risks with different forms, probabilities and impacts (Er Kara and Oktay Firat, 2016). The first step of SCRM is the identification of risks (Hallikas et al., 2004). Hence, a literature review is performed to investigate different SC risks and their driver/triggering factors. A list of possible risk factors is created by compiling the articles and practical studies relevant to SC risk. The determined risk sources are gathered together in an excel table with their references and frequency in the reviewed articles. This table is provided to facilitate the identification of possible disruptive events in SCs and develop a comprehensive risk classification.

The categorization of SC risks is necessary in order to apply specialized strategies and methods to deal with each group of risks (Solomon et al., 2012). Although many studies tried to list and classify SC risks, there is a need for a more comprehensive and multi-dimensional view of SC risks. We aim to try to construct a new classification for SC

risks in this section. The proposed categorization is also used in the identification of SC risks in the application part of the study.

The literature review aims identifying the SC risks that are most mentioned and studied in the SC risk literature. The main focus of the study is to bring together different uncertainties and risks in SCs. It will strengthen the understanding of SC risks, their rippling effects and the relationships between different risk sources. In addition, it will help to investigate the current trends and issues in SC risk. We tried to make a comprehensive review on articles and recorded the encountered risks and their root sources in an excel table. The searches are conducted via ScienceDirect, Emerald and IEEE databases, and 250 journal articles on the SC risk topic between 1997-2015 are collected. We used “supply chain risk” and “supply chain risk management” keywords for searching the titles, keywords and abstracts of articles. In addition, some references of the collected papers are reviewed. We have reviewed 37 articles between 2004-2015 years. Figure 3.2 shows the number of reviewed articles according to year.

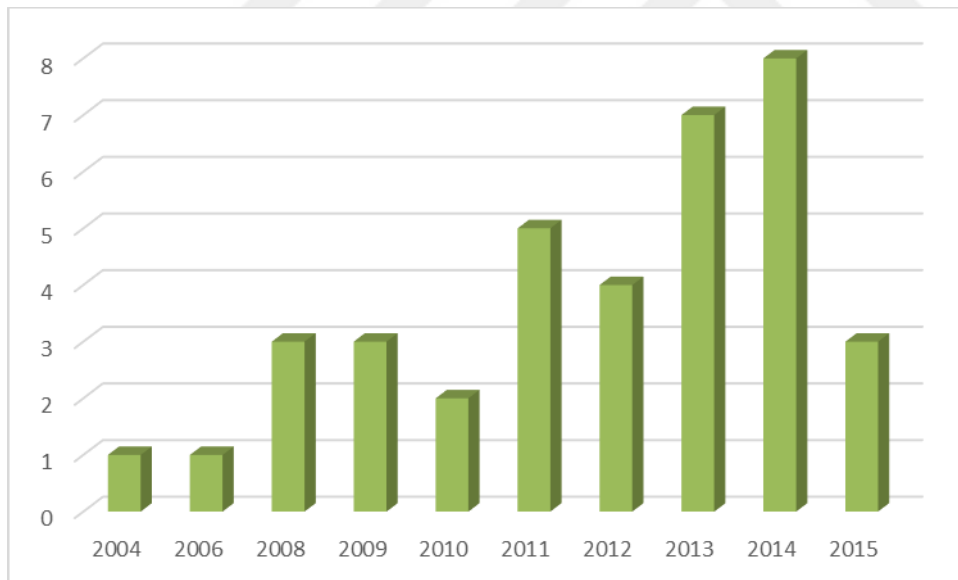


Figure 3.2. The number of reviewed articles according to year

We reviewed those papers that can contribute to our classification. Different sources of risks are then categorized in a unique framework to generate a general overview and understanding on SC risks. Figure 3.3 shows the number of reviewed articles according to the journals.

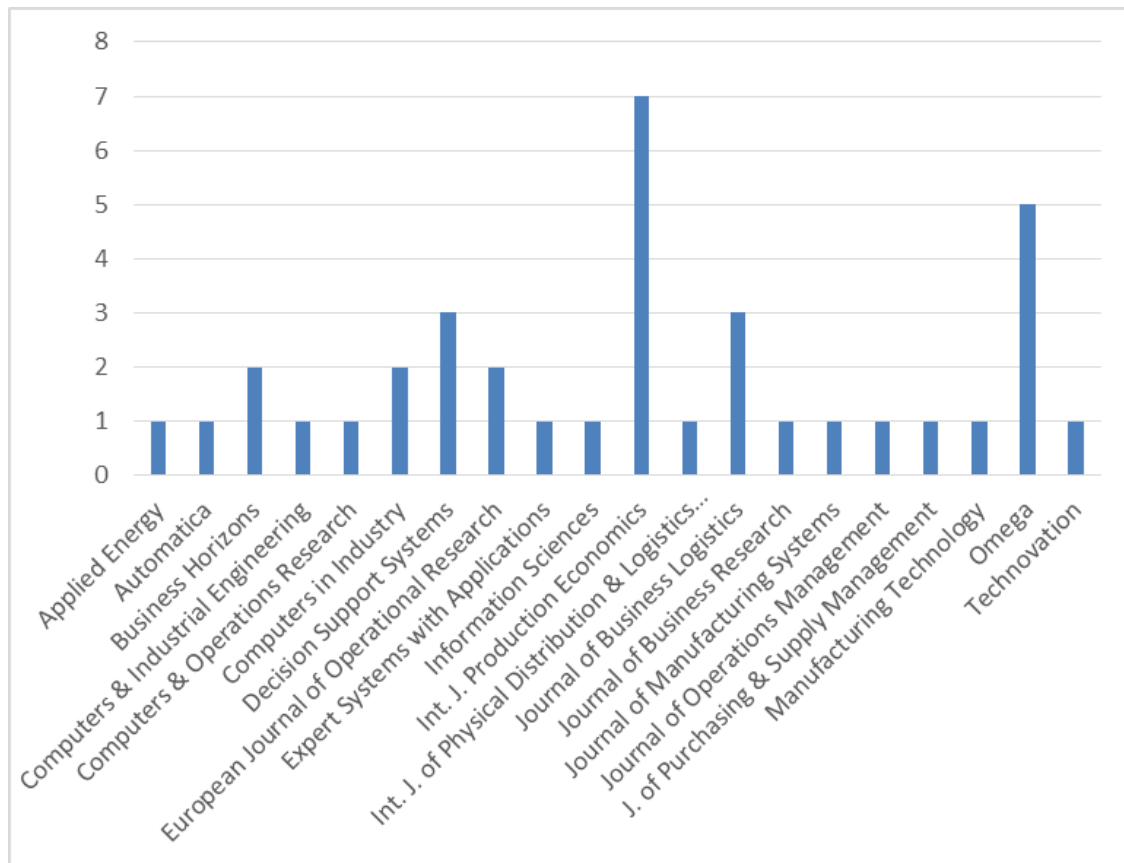


Figure 3.3. The number of reviewed articles according to the journals

3.3.2. Literature Review on Supply Chain Risks

Supply chains are exposed to various types of internal and external risks. SC literature is rich of studies on these risks (Er Kara and Oktay Firat, 2017b). Most of the studies focus on frequent and low impact risks (Oke and Gopalakrishnan, 2009; Bradley, 2014). Demand and supply uncertainty are the most studied SC risks in the literature (Er Kara and Oktay Firat, 2016). Chen and Seshadri (2006) discussed demand risk and its impact on ordering decisions and then applied optimal control theory to solve the contract design problem in which the retailers have different degrees of risk aversion. According to their results, the channel structure is determined by the distribution of the risk aversion and the demand independent of the underlying contract. Especially the industries in which the products have short lifecycles or are perishable such as food are the most vulnerable to demand uncertainty (Chen and Seshadri, 2006).

Supply and demand may fluctuate for various reasons. Supply-demand imbalance is a major risk especially for the industries in which capacity is expensive. Tomlin (2014) proposed mix flexibility as an attractive solution to decrease supply-demand risk and absorb capacity fluctuations. Tabrizi and Razmi (2013) gave a table providing a review on twenty papers that dealt with uncertainty and most of the studies took demand, supply or process as uncertain parameter(s).

Trkman and McCormack (2009) proposed a framework for the assessment of supplier risk by considering the effects of the endogenous (market and technology) and exogenous turbulence on the relationship between supplier's attributes, performance of the SC and the disruptions. Besides separating the uncertainties as endogenous and exogenous uncertainty, they divided exogenous risks into discrete events (including terrorist attack and employee strikes) and continuous risks (e.g. changes in raw material prices or inflation rate). Their framework is given in Figure 3.4 and represents the position of a supplier according to its performance and the turbulence of its environment.

Supplier performance in a chain	High	Rock: high performer in a stable environment	Star: high performer in a turbulent environment
	Low	“millstone”: low performance in a non-turbulent environment	Bouncer: low performance in a turbulent environment
		Low	High
		Endogenous & exogenous uncertainty	

Figure 3.4. Supplier performance and uncertainty matrix (Trkman and McCormack, 2009)

Sawik (2013) proposed a new mathematical programming approach to select resilient supply portfolio under SC disruption risks. In this approach, selected suppliers are protected against disruptions and emergency inventory is allocated among the protected

suppliers. Sawik (2013) also mentioned from independent local disruptions associated with a particular supplier such as equipment breakdowns and local natural disasters; and global disasters that may affect all suppliers simultaneously such as economic crisis, widespread labor strike in a sector, etc. Fang et al. (2013) made a similar categorization and evaluated the ability of alternative sourcing strategies (i.e., single, dual, multiple and contingent sourcing) to cope with both disruptions that result from major events and recurrent risks that have high probability and low impacts.

SC disruptions may also arise because of the failures of lower levels of suppliers in the SC. An oft-cited example is the fire at Ericsson's sub-supplier in 2000. Norrman and Jonsson (2004) gave a detailed description of Ericsson's SCRM approach after this accident. The new approach contains the analysis and management of risk sources related to the company as well as its suppliers and sub-suppliers. Airmic Technical (2013) reported that 60% of disruptions related to the potential failure of all suppliers is caused by tier 1 suppliers, 30% by tier 2 suppliers and the remaining 10% by tier 3 suppliers. In their SC insurance market review, they also stated that fire and flood are major causes of disruption; and chemicals, pharmaceutical, food and motor manufacturing are the business sectors in which SC risks can easily be identified.

Outsourcing risk is another common risk type in SCs. Today an increasing number of companies add the manufacturers at low cost locations (such as China and India) to the geographical scope of their sourcing activities. Although outsourcing decreases the manufacturing costs and improves the responsiveness, the distribution of the functions of an organization to different regions or suppliers brings new uncertainties (Tang and Musa, 2011). Wu et al. (2013) developed a stochastic fuzzy multi-objective programming model for SC outsourcing risk management in which internal operating risks such as demand and supply risks are modeled by using probability distributions and external risks such as economic environment and vendor ratings is expressed in fuzzy data. Their results indicate that a more risk-averse customer prefers to order less under uncertainty and risk.

Companies hold inventory and this may cause a significant risk under demand and market uncertainty. Lai et al. (2009) investigated the impact of financial constraint on the choice of SC modes: preorder, consignment and combination modes in which the

retailer, supplier and both taking the inventory risk respectively. Takata and Yamanaka (2013) focused on the potential risks associated with the parts of products and proposed a method to evaluate these risks and the applicability of countermeasures based on bill of material.

Tuncel and Alpan (2010) investigated the disruption factors of the SC network by a failure mode, effects and criticality analysis (FMECA) technique and used Petri net based simulation to analyze the effects of various disruptions (demand, quality, transportation, etc.) and mitigation actions on the overall system's performance. Failure modes in the FMECA table are gathered from expert interviews, brainstorming and cross-functional teams. The identified fourteen common SC disruptions are classified in supplier, inbound/outbound logistics, manufacturer and customer groups. Lavastre et al. (2012) made an empirical study of 142 general managers and logistics & SC managers in 50 different French companies. They tried to understand and analyze how organizations are structured and managed to cope with SC risks. The findings of their empirical study suggest collaboration and the establishment of joint and common traverse processes with industrial partners for an effective SCRM. Claypool et al. (2014) applied a survey to industry experts to evaluate 29 SC risk factors and 21 New Product Development risk factors that are identified by their literature review. They selected the risk factors with the highest points (on both likelihood of occurrence and impact criteria) to include in their Design for Supply Chain model. Selected risk factors are strategic exposure risk, market/demand risks, capacity risk, supplier reliability, and time-to-market risk.

Vilko and Hallikas (2012) studied on the assessment of risks and their effects in a multimodal maritime SC. They made interviews to identify the uncertainties in multimodal SCs and applied Monte-Carlo based simulation to evaluate the delay effect of the risks. The sensitivity analysis of the major risk drivers that lead to delay variation are represented in Figure 3.5. They also emphasized the importance of time in the transportation of time and temperature sensitive products such as fresh food and medicine.

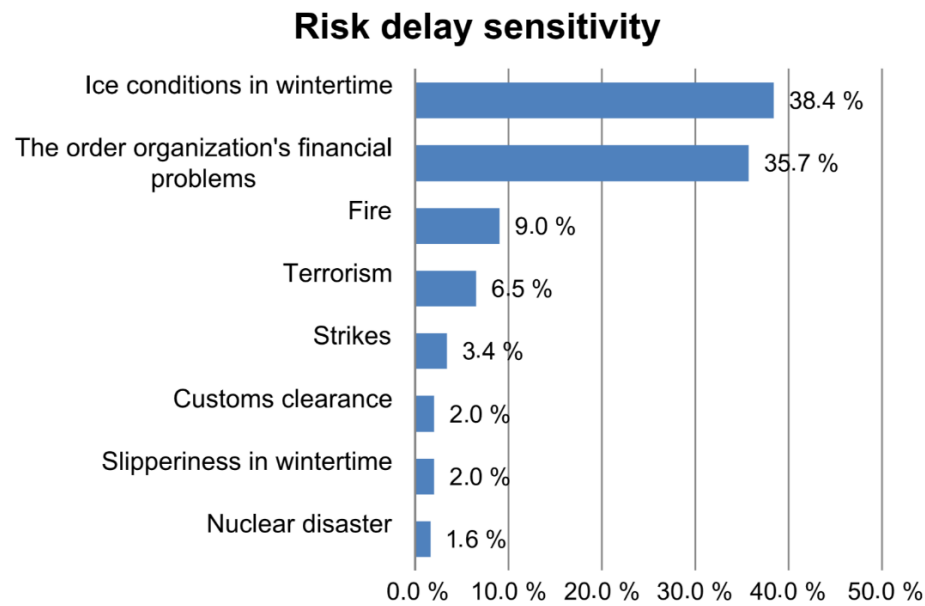


Figure 3.5. The sensitivity analysis of risk drivers that lead to delay variation (Vilko and Hallikas, 2012)

Thun and Hoenig (2011) made an empirical analysis on SC risks in German automotive industry. The results of their survey show that the top three developments that lead to SC risks are globalization, product variants, and outsourcing. They also depicted various risks in a “probability-impact” matrix as in Figure 3.6.

Recent technological developments and globalization of IT technologies bring risks as well as opportunities. Boyson (2014) listed some of the risks that disrupt IT systems as follows: cyber-attacks, unauthorized access, counterfeit products and sales, "report-back mechanisms" embedded to hard drives, malwares and viruses, fraud by employees, software integrity threats and regulatory risks. He also provided a survey on Cyber Supply Chain Risk Management (CSCRM) that aims to assess and mitigate risks in SCs of IT networks, hardware and software systems (IT supply chain/cyber SC).

Tang and Musa (2011) categorized SC risks under three headings: material, cash and information flow risks. They also stated that there is a research gap for analyzing information flow risks in the literature. Le et al. (2013) examined the risk caused by sensitive knowledge leakage in retail SC collaboration.

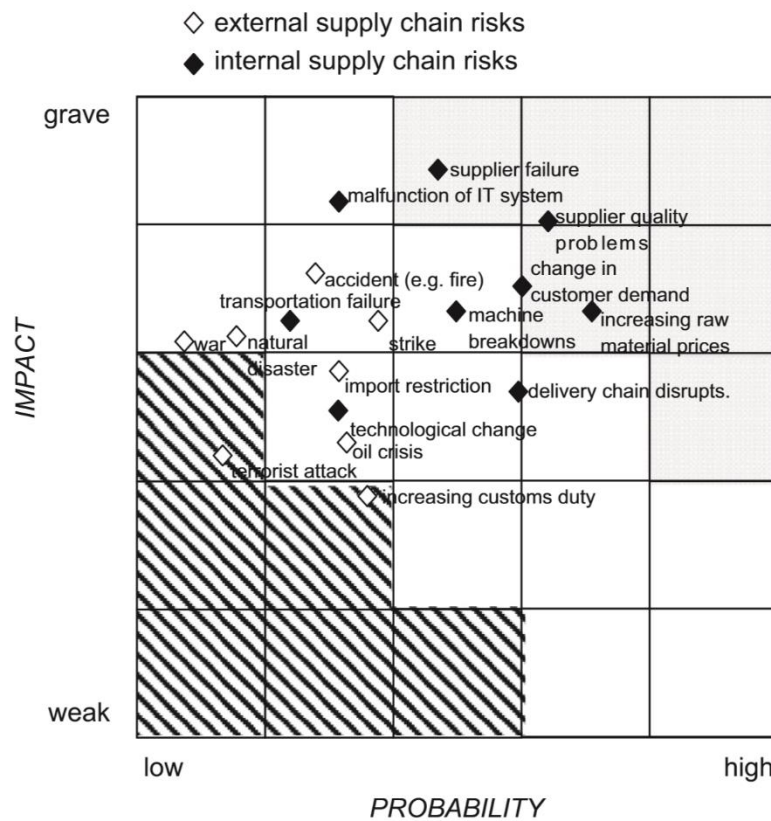


Figure 3.6. Supply chain risks (Thun and Hoenig, 2011)

Today various researchers started to incorporate sustainability concept into risk management. We refer to Er Kara and Oktay Firat (2017a) for a comprehensive review on the relationship between risk management and sustainability. Sustainability concept provides a broader view for ERM by including social and environmental considerations and thus increases the responsiveness of the companies to emerging risk areas (WBCSD, 2013; AON, 2007).

The risk issues emerged with the consideration of sustainability concerns are referred as sustainability risks (or sustainability-related risks) by some researchers (AON, 2007; Lam and Quinn, 2014). Sustainability risks consider the three pillars of sustainability and include the risks related with the environmental, economic and social hazards. Examples to these risks include; global warming, climate change, resource scarcity, job safety, damage to corporate's reputation, social justice, salary fairness, etc. (AON, 2007).

Giannakis and Papadopoulos (2016) identified 30 risks under the three main pillars of sustainability through literature review and interviews. They also applied failure mode

and effect analysis (FMEA) to identify the root causes and effects of sustainability-related risks and assess these risks and their inter-relationships. The most important risks are listed as follows: greenhouse gases, natural disasters, child/forced labor, financial crisis, bribery/corruption, pollution, non-compliance with sustainability laws and energy consumption. According to World Economic Forum Supply Chain and Transport Survey in 2011, disruptions are categorized in four risk categories: environmental, geopolitical, economic and technological risks (World Economic Forum Report, 2012). The first three risk categories took higher ranks.

According to the report of WBCSD published in 2017, discussions and surveys with risk management and sustainability practitioners show that 89% of the respondents agree that sustainability risks could lead to a significant impact on business. However, 70% of the respondents think that risk management practices are inadequate to address sustainability risks. There are various reasons that decrease the efficiency of sustainability risk management including lack of sufficient knowledge about sustainability, not considering sustainability opportunities in risk management, lack of collaboration between sustainability and ERM functions, and the length of timeline required to measure and track sustainability risks (WBCSD, 2017). The importance and criticality of sustainability risks have been increasing due to the increased importance of sustainability issues, rapidly changing standards and regulations, and increased awareness and expectations of stakeholders and public on sustainability (AON, 2007). Lintukangas et al. (2016) performed an empirical study to examine the linkages between green supply management practices and different supply risks: property rights, image, outsourcing, quality and price.

Financial risk has taken increased attention since the global financial crisis in 2007 (Liu and Cruz, 2012). Especially exchange rate uncertainty is one of the most important concerns of global companies. Liu and Nagurney (2011) studied the impacts of foreign exchange risk and competition intensity on SC companies that have different risk attitudes and are involved in offshore-outsourcing activities. They also emphasized the risks arising from offshore-outsourcing including foreign exchange risk, production disruption risk, quality risk, supplier default risk, etc. Liu and Cruz (2012) developed an analytical framework and investigated the effects of financial risks and economic uncertainty on the SC firms' values, profits and decisions. They proposed to incorporate

exchange rate risk and supply disruption risk to their model for a possible future direction. Mulhall and Bryson (2014) focused on the risks associated with the energy price volatility. According to the MIT/PricewaterhouseCoopers Global Supply Chain and Risk Management Survey, the top five sources of risks are; raw material price fluctuation, currency fluctuations, market changes, energy/fuel prices volatility and environmental catastrophes (PwC&MIT Forum, 2013).

There are also some rare risks such as natural disasters, strikes, wars and terror events. These disruptions cannot be estimated precisely and arise without a warning. They generally cause severe and unsettling negative results. Bradley (2014) compared frequent versus rare, catastrophic disruptions in SCs and proposed a new risk measurement and prioritization method for rare risks. Historical data and observations about catastrophic risks are generally insufficient; hence, interviews and brainstorming methods may be used in identifying these rare risks. According to a survey performed by Ambulkar et al. (2015), out of 199 disruptions that are faced by the companies; 62 were supply glitches/disruption, 42 were logistics/delivery glitches, 44 were in-house plant glitches, and 51 were natural hazards, regulatory issues, or political issues.

There are various classifications of SC risks based on different aspects such as frequency, impact, source and triggering factors (Er Kara and Oktay Firat, 2017b). Waters (2011) analyzed SC risks in several ways in his book and gave a review for different classification systems for risks. The first one classifies SC risks as internal and external risks. Internal risks are controllable risks such as poor forecasts, late deliveries, human errors, breakdowns, etc. External risks are caused by the outside factors such as earthquakes, hurricanes, wars, problems with partners, crime, etc. Although internal risks are common, external risks are rare. Second classification is done by the flows of materials, money and information in a SC and the ways these flows are organized: physical risks, financial risks, information risks, and organizational risks. Peck et al. (2003) classified the sources of risks under three categories: i) internal to the focal firm (process and control), ii) external to the focal firm but internal to the SC network (demand and supply), and iii) external to the network (environment).

SC risks can also be classified as unsystematic and systematic risks (Brindley and Ritchie, 2004; Kar, 2010). Systematic risks arise from unpredictable and unavoidable

factors such as inflation. Differently from systematic risks, unsystematic risks are often generated by the decisions of organizations. Harland et al. (2003) combined different types of risks and various authors' definitions in their study. These risk types include strategic, operations, supply, customer, reputation, financial, fiscal, regulatory, and legal risks.

Zsidisin and Ritchie (2009) categorized the risks in SCs under four dimensions: disruptions of the supply of goods or services, price volatility, poor quality products or services, and reputation of the firm. According to Chen and Wu (2013), there are four types of risks in SCs: demand, due date, cost management, and risks associated with production capability and operation flexibility. Manuj and Dittmann (2012) categorized risks into cost risks, quality risks, lead-time risks and security risks according to interviews with professionals dealing with global sourcing.

Kar (2010) listed the sources of risks as environmental, industry, organizational, domain specific and decision maker related risks. Maclean-Bristol (2008) classified the threats to SCs in six categories: environmental, social, legal, political, economic, and technical risks. Sodhi and Tang (2012) considered three types of risks motivated by the SC organizations: supply risks, process risks, demand risks and corporate-level risks (financial, political and social issues, etc.). Olson (2012) gave a table that represents specific SC risks considered by various studies. The considered risks were classified in external and internal categories. External risks contain natural events and political issues. Internal risks have three main classes; available capacity, internal operation and information system.

3.3.3. Literature Review Findings and Discussion

Possible risks and uncertainties and their sources that are mentioned and studied in the literature are determined through literature review. Figure 3.7 gives a list of the most frequent SC risks and uncertainties that appeared in the reviewed articles. Although the uncertainties vary according to the process, company or sector, some of them are mentioned in most of the studies.

Most of the risks in Figure 3.7 are interconnected and some disruptions may be incorporated into more than one category. For example, the failure of a machine that is

used in the manufacturing of a part can be classified into both process and technological risk categories. In addition, a disruption may cause other disruptions or even cause a ripple effect. There are relations in both inter and intra- clusters. The sub-components of disruption sources may fluctuate by one or more. For example, an earthquake may affect only one supplier, or all the suppliers, manufacturers and the customers in the SC network.

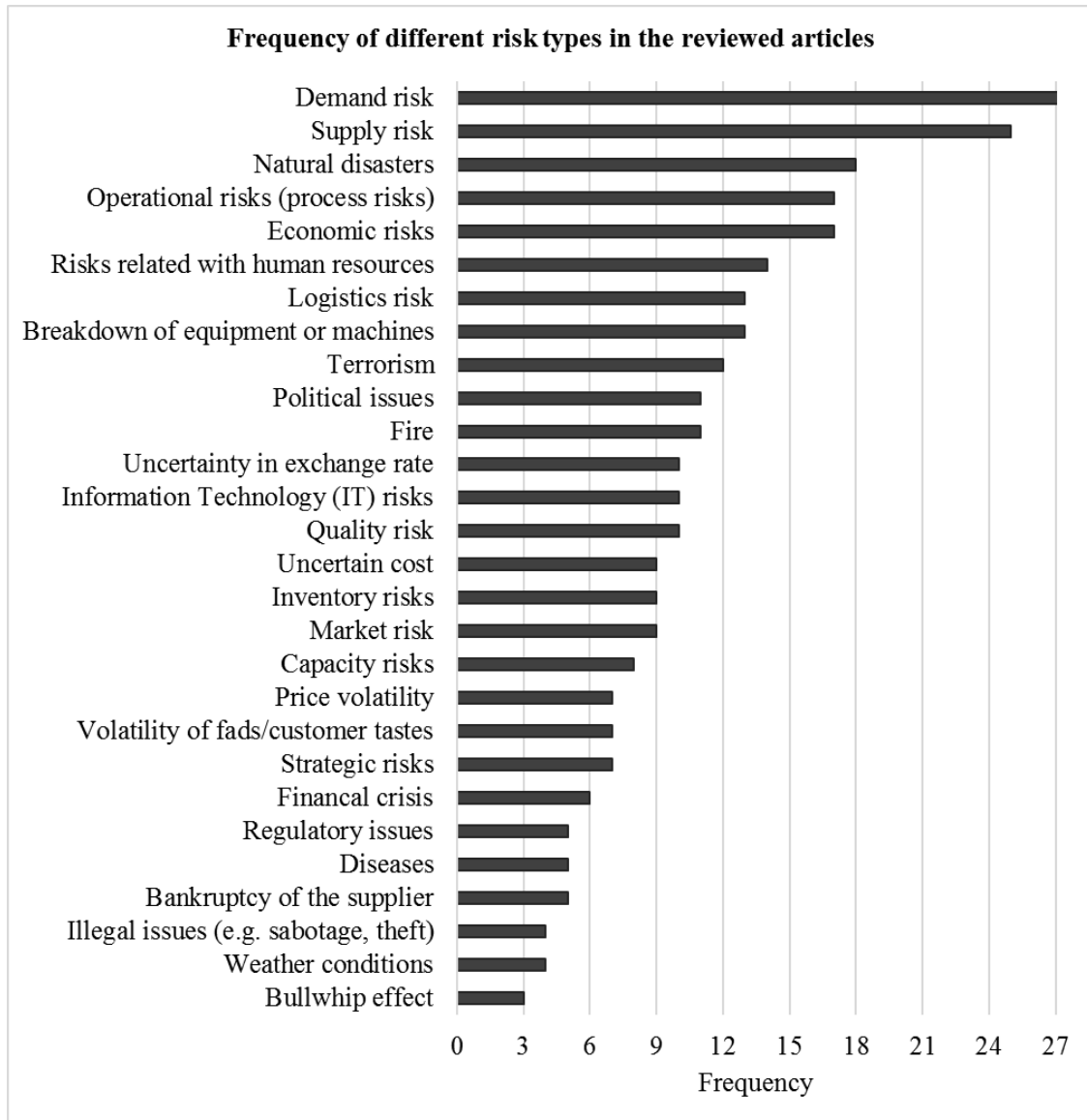


Figure 3.7. Main risk issues discussed in the reviewed articles

According to the literature review, the following results have been concluded:

- Studies generally focus on frequent and low-impact risks but ignore low-frequent high-impact risks (Chopra and Sodhi, 2004). Unavailability of sufficient data about rare risk events makes it very difficult to estimate the probability and impact of these events. Therefore, despite the awareness of rare risks, the number of studies that incorporate these risks in their SC risk models is very few (Bradley, 2014). New methods are needed to identify, measure, prioritize and manage rare SC risks.
- Some of the rare/catastrophic risks cannot be foreseen. Therefore, contingency plans must be developed to respond to these events emergently when they occur. Hence, the impact of these risks can be reduced.
- Besides their own risks, companies should also consider the risks in other members in their SC.
- Risk aversion is an important factor affecting the orders of the customers and retailers. Therefore, it should be considered in analyzing demand risk.
- Most of the studies in SC risk area focus on supply risk (Trkman and McCormack, 2009; Tang and Musa, 2011).
- Outsourcing is a popular risk that has been studied in a lot of publications. Especially, the tendency of outsourcing to low cost countries increased this type of risk.
- The supplier selection is a complex and stochastic optimization problem. A lot of studies in the literature studied on solving this problem under disruption risks (Wu et al., 2013; Sawik, 2013). The suppliers' risk and the turbulence of their environment should be considered in selecting and managing suppliers (Trkman and McCormack, 2009). Supplier selection in offshore sourcing is also much riskier than in domestic sourcing because there are exogenous risk factors influencing offshore sourcing (Wu et al., 2013).
- Interconnectedness in global SC networks can cause small and local events to grow and result in significant disruptions. Therefore, collaboration and transparency across SC actors is very important.
- Risk effects can be categorized in time-based, finance-based and quality based types (Vilko and Hallikas, 2012).

- Many researchers focus on risks associated with material flows. Another risk sources such as information flow risks should be considered in SCM decisions (Tang and Musa, 2011).
- Most of the studies in the literature focus on dyadic risk management, but the risks in the sub-tier supply networks should be considered too (Basole and Bellamy, 2014).

There are numerous sources of risks in SCs; hence, it is not possible to list all of the conceivable risks. SC risk drivers are examined by their source and combined under 11 groups. Table 3.3 summarizes the proposed classification of SC risks. Risks may arise from endogenous and exogenous sources. Endogenous sources contain the firm, its suppliers and customers. Exogenous sources include environmental, political and economic issues. The proposed classification can be used as a guide to discover the types of disruptions. The table provides an integrated view of SC risks and their sources. For a more comprehensive SC risk classification, we refer to Er Kara and Oktay Firat (2017b).

3.4. Supply Chain Risk Management

This section introduces SCRM process and gives a literature review on the strategies and methods used in this area.

3.4.1. Introduction to Supply Chain Risk Management

An efficient SCRM plays an important strategic role for companies. This section gives an overview of SCRM process and its main steps. In addition, some key principles are given for a successful risk management in SCs.

SCRM is the implementation of strategies to identify, assess and manage risks within SCs for reducing vulnerability and ensuring the sustainability of SCs (Jüttner, 2005; Tang, 2006). SCRM has gained attention in the late 1990s with the occurrences of SC risk events such as the fire in Philips Semiconductors' New Mexico plant in 2000 (Takata and Yamanaka, 2013). Risk management within SCs is one of the vital issues for every organization in a SC.

Table 3.3. Proposed Classification for SC Risks and Uncertainties

Risk categories and sub-risk factors	
Economic Risks	Management or Facility related Risks
Volatility in price	Strategic risks
Uncertain cost	Policy risks
Exchange rate risk	Organizational risks
Financial crisis	Poor forecasts
Supplier-related Risks	Network related risks
Delays in delivery of raw materials/parts	International business risks
Changes in raw material prices	Customer and Market Risks
Poor supplier selection process	Quality problems
Supplier market characteristics	Changes in customer tastes
Quality risk	New product adaptations
Location of the supplier	Market volatility
Failure of information	Regional differences in customers
Technological changes	Bankruptcy of the customer
Manufacturer Risks	Industry-related Risks
Inventory risk	Industry capacity
Operational/process risks	Industry/market risks
Capacity risk	Industry regulations
New product development risk	Product/service obsolescence
Breakdown of equipment/ machine/ machinery	Exhaustion of raw materials
Lead time uncertainty	Technological Risks
Labor issues	Information system failures
Varying holding cost	Cyber risks
Logistics Risks	Technology change
Transportation failures	Environmental Risks
Long distances	Natural disasters
Port stoppage	Severe weather conditions
Technical problems with transportation vehicle	Fire
Legal and Illegal Issues	Explosion
Export/import restrictions	Diseases
Sabotage	Environmental pollution
Criminal activity	Regional Risks
Theft, Hijacking	Political issues
Maritime piracy	Social risks
People-smuggling	Geographical position
Spying and espionage	Country risks

SCRM is the intersection of SCM and risk management. The aim of SCRM is to understand the risks and their effects, and try to take proactive and preventive actions for risks. The goal of enterprises to use SCRM systems is to have resilient SCs that can handle with disruptions (Solomon et al., 2012). SCRM contains the strategies, systems, policies and tools that are used to minimize risks within a SC. SCRM can deal with risks of a company or focus on a single activity. According to Hallikas et al. (2004), a typical risk management process has four main steps:

- i) Risk identification
- ii) Risk assessment
- iii) Decision and implementation of risk management actions
- iv) Risk monitoring

These steps should be applied iteratively and on a continuous basis (Souza et al., 2003). Each of these steps is explained in the following:

Risk identification: This is the first step to manage SC risks. All possible risk events, their causes and consequences are determined in order to understand and manage future uncertainties. There are many ways to identify and categorize risks such as interviews, surveys and FMEA (Gill et al., 2008; Chen and Wu, 2013; Fowler, 2014).

Risk assessment: Risk assessment step includes the evaluation of the risks (identified in the previous step) according to their likelihood and consequences. The potential negative impacts of the risks must be considered to balance different types of risks. Risk assessment step is critical, because its results influence the decisions of the organization (Sodhi and Tang, 2012). Companies allocate their funds to different risk mitigation efforts according to the results of the risk assessment step. Risk identification and assessment steps show where to focus our actions.

Elkins et al. (2004) gave some suggestions for companies to identify and assess manufacturing and SC risks. First, a portfolio map of enterprise risks is generated containing financial, strategic, hazard and operational risks. Secondly, this portfolio is filtered down to the risks related with manufacturing and SC operations. Then a subjective risk map is constructed based on expert opinions and risks are classified based on their probability and severity. Figure 3.8 represents an example subjective risk map. The prioritized risk map can guide in identifying the top priority risks.

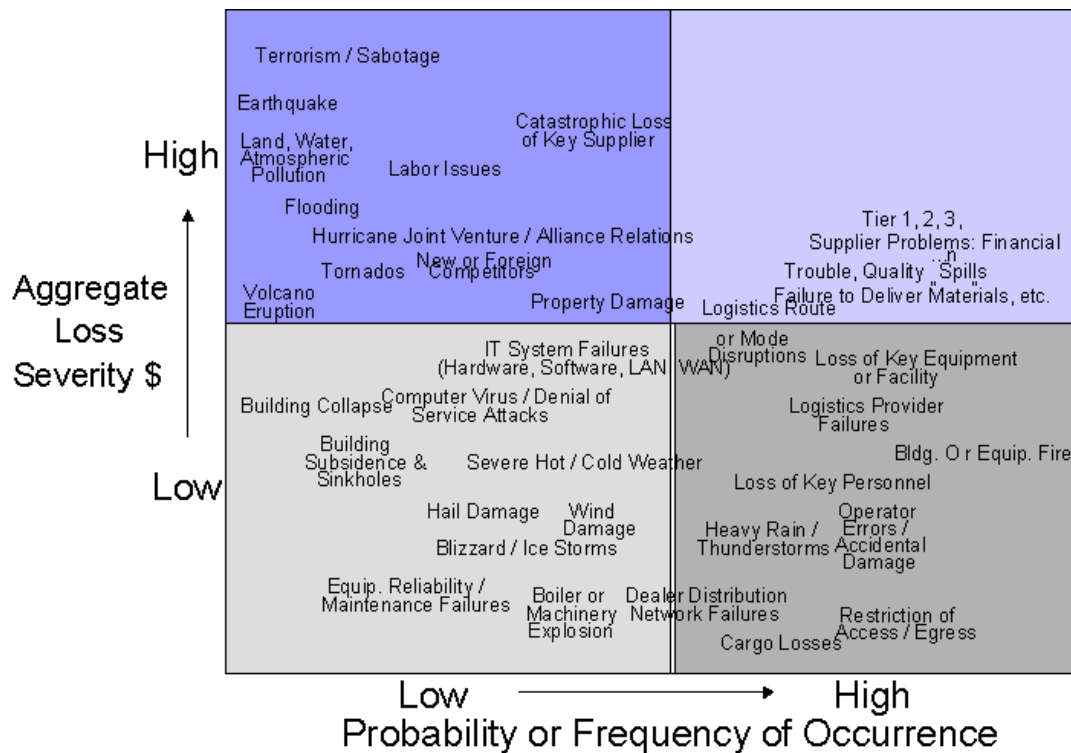


Figure 3.8. Example subjective risk map (Elkins et al., 2004)

Sodhi and Tang (2012) suggested using a butterfly depiction of SC risks to clearly separate causes and effects (Figure 3.9). The body of the butterfly includes risk events. While the left-hand wing represents the underlying causes and prevention efforts, the right-hand wing represents the post-event impact and response efforts.

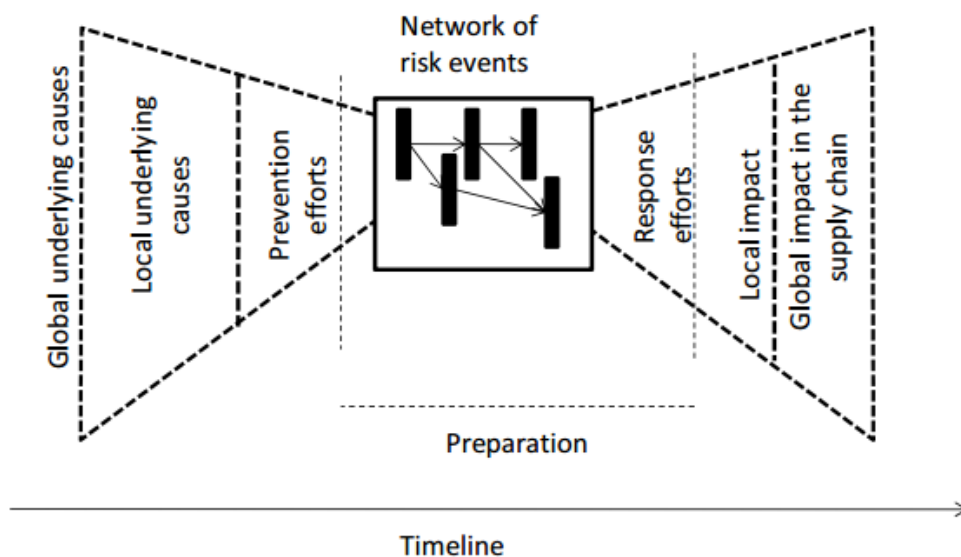


Figure 3.9. A butterfly depiction of risk with a network of risk events (Sodhi and Tang, 2012)

Decision and implementation of risk management actions: This step finds answers to the following questions (Er and Oktay Firat, 2014):

- i) Which method will be used for risk management?
- ii) How and when the risk management strategy will be implemented?
- iii) Who is responsible for the management of the selected risks?
- iv) What are the requirements (staffing, financial, etc.) for the selected risk management action?

There are different ways to respond to risks including risk transfer (e.g. transfer risks to an external agency such as an insurance company), risk taking, risk elimination, risk reduction, risk sharing and further analysis of individual risks (Hallikas et al., 2004). Souza et al. (2003) proposed four basic approaches to mitigate the impact of SC risks: supply management, demand management, product management, and information management.

Risk monitoring: SC is a dynamic network; hence, the changes in the likelihood and consequences of risks and the existence of new risk factors should be monitored in order to identify and respond to them quickly.

The mentioned four steps of Hallikas et al. (2004) are common in most of the studies in the literature: identification of risks, assessment of risks, risk management actions, and monitoring risks. Some of the researchers add extensions to these steps to provide new measures and enhance the SCRM process. Souza et al. (2003) add risk measure, disruption risk management, toolkits/stochastic models, solution method and operational risk management to the basic steps of SCRM. This framework covers both operational and disruption risk management.

Musa (2012) divided SCRM into two main elements; SC risk analysis (risk assessment) and risk control as in Figure 3.10. Risk analysis process contains the identification, estimation and evaluation of risks. Risk control constitutes of risk mitigation and risk monitoring steps.

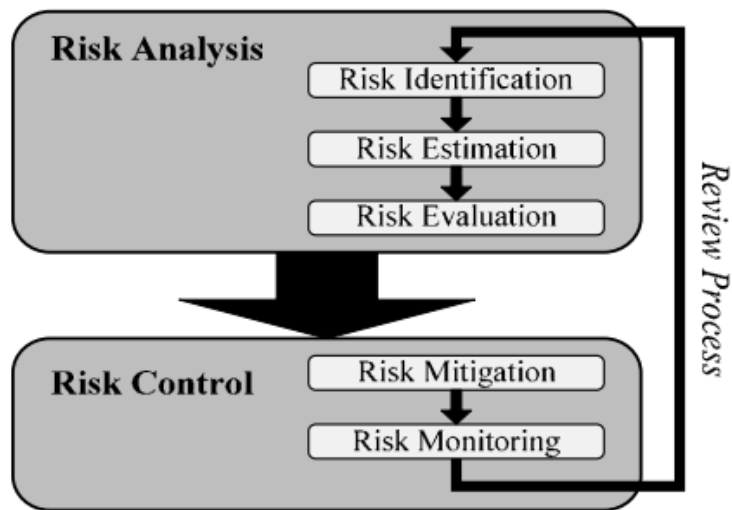


Figure 3.10. Supply Chain Risk Management process (Musa, 2012)

Supply Chain Risk Leadership Council (2011) represented SCRM process as in Figure 3.11. The proposed framework starts with the identification of internal and external environments. Communication and monitoring processes are performed during all of the steps of the proposed framework.

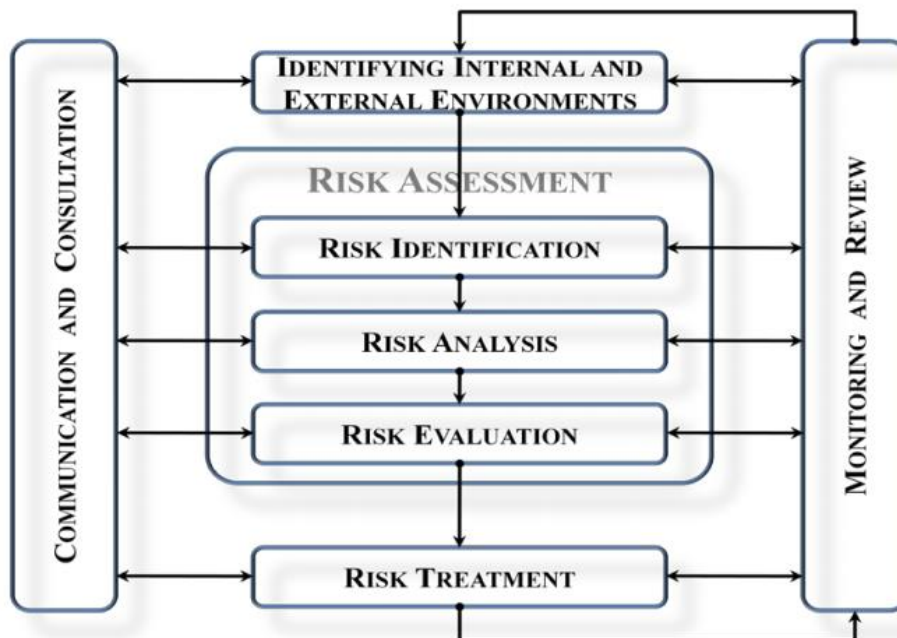


Figure 3.11. Risk management process (Supply Chain Risk Leadership Council, 2011)

Revilla and Sáenz (2014) combined the risk assessment and mitigation steps in one-step and called it disruptions management. They also added a learning feedback to their disruption management framework that represents the learning of SCs from past disruptions in the network.

Hallikas et al. (2004) suggested a risk management process in a network environment as shown in Figure 3.12. According to their model, each partner of the network should have its individual risk management process and these processes should be combined by a collaborative process. Khan and Zsidisin (2012) analyzed the general structure of a risk management process in three stages: risk identification, risk analysis and risk evaluation. Olson (2012) analyzed SCRM process in risk identification, risk assessment, risk avoidance, and risk mitigation steps.

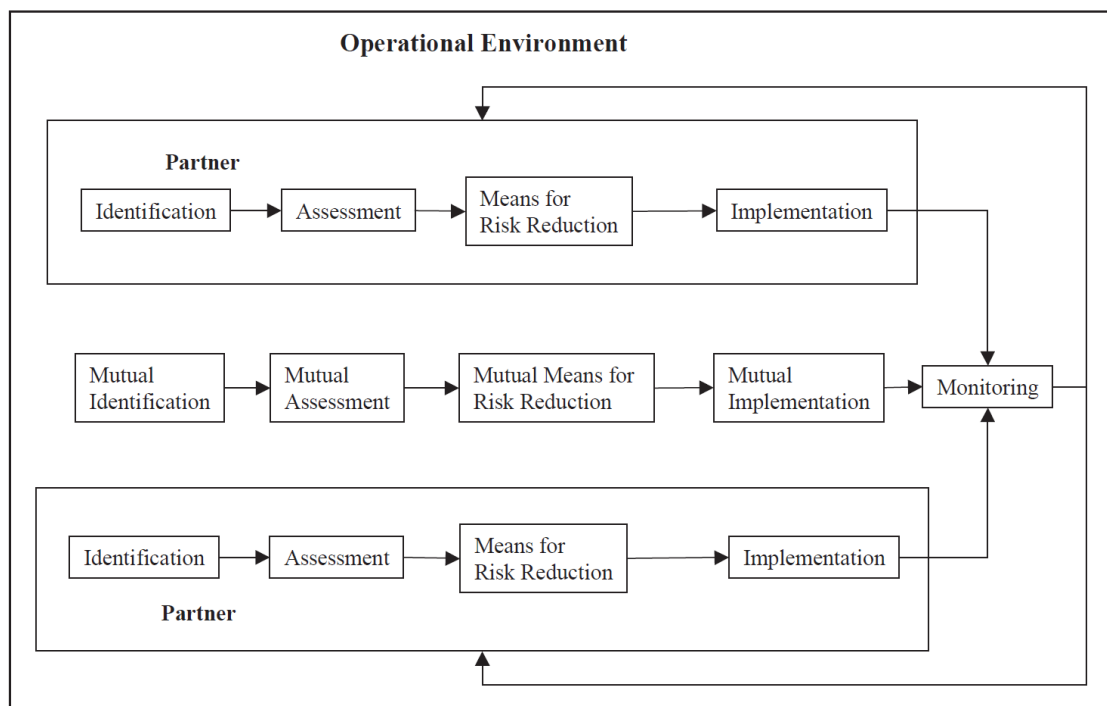


Figure 3.12. Risk management process in network environment (Hallikas et al., 2004)

Norrman and Lindroth (2004) examined logistics and SCM risks in three dimensions; the logistics unit of analysis, the type of risk/uncertainty and the risk management activity. They constructed a conceptual framework by combining these dimensions in order to categorize different SCRM issues.

The MIT&PwC Forum for Supply Chain Innovation has released a report, “Making the right risk decisions to strengthen operations performance”, based on the results of its 2013 Global Supply Chain and Risk Management Survey (PwC&MIT Forum, 2013). Five key principles are proposed in the report for a better risk management in SCs:

- 1) SC disruptions effect companies’ business and financial performance.
- 2) A good SC and risk management make companies more resilient to SC disruptions.
- 3) Invests for SC flexibility make companies more resilient to SC disruptions.
- 4) Invests for SC segmentation make companies more resilient to SC disruptions.
- 5) Companies that have mature capabilities in SCM and risk management are better in all dimensions of operational and financial performance.

3.4.2. Techniques and Applications in Supply Chain Risk Management

There is a wide variety of SC risks resulting from multiple sources. Therefore, different tools, techniques and strategies are required to cope with these disruptive events in SCs. We refer to Er and Oktay Firat (2014) for a literature review on SCRM methods. Kajüter (2003) divided SCRM literature into two groups: i) mathematical models that are used to analyze risk-sharing instruments, ii) conceptual studies in SCRM by exploratory case studies. There are a lot of studies in the literature about the risks and uncertainties in SCs. Different models, tools and techniques have been developed to understand and manage SC risks. Various studies have been done in different sectors such as aviation (Rashid, 2014) and energy industries (MS, 2014).

SCRM literature can be examined according to the studied risk types, the stage of SCRM and the method used in the study. While some of the authors focus on the identification and assessment of SC risks, some researchers focus on the methods and strategies for the mitigation of SC risks. Schoenherr et al. (2008) used the Analytic Hierarchy Process (AHP) to evaluate the importance of a set of risk factors and determine the best alternative. Neiger et al. (2009) studied on incorporating risks into business objectives and proposed a SC risk identification methodology based on value-focused process engineering. Tuncel and Alpan (2010) investigated the disruption factors of the SC network by a Failure Mode, Effects and Criticality Analysis (FMECA) technique. Then they proposed a Petri net based modeling framework to model the SC

network, analyze the effects of various risks on the system's performance and evaluate mitigation actions. The results of their real industrial case study show that the system performance can be improved by using risk management. Vilko and Hallikas (2012) presented a new categorization of risks and their effects in multimodal maritime SCs. Then they analyzed the delay impact of risks with Monte-Carlo based simulation. The impact of SC disruptions may be estimated with different methods; e.g. simulation and optimization models (Knemeyer et al., 2009).

The representation of uncertain parameters is an important topic in decision-making. Gupta and Maranas (2003) introduced two methodologies to represent uncertainties: i) distribution-based approach in which potential consequences are represented with probability distributions, ii) scenario-based approach in which uncertainties are described with a set of scenarios. Tabrizi and Razmi (2013) developed a mixed-integer non-linear mathematical model in which the uncertainties are represented by the fuzzy set theory. The problem was solved by applying Benders decomposition and the model was transformed into a mixed-integer problem.

SC practitioners have various choices to deal with the risks in SCs. Some of the countermeasures for risk prevention and mitigation in the literature are listed in the following (Norrman and Jansson, 2004; Trkman and McCormack, 2009; Tuncel and Alpan, 2010; Thun and Hoenig, 2011; Xia and Chen, 2011; Lavastre et al., 2012; Sawik, 2013):

- Mitigate the impact of disruption risks by minimizing the potential worst-case,
- Relocation of the facility away from high risk location; e.g., moving a warehouse to a hurricane-free area, redesign of the facility to increase storm preparedness, building storm walls to help protect against flooding, maintaining excess inventory, etc.
- Avoidance, reduction, weakening, separation, sharing and transfer of risks,
- Improved collaboration with customers and suppliers by timely and relevant information exchange,
- Co-operation and integration with suppliers,
- Increasing flexibility of products and operations,
- Dual-sourcing or multiple-sourcing strategies,

- Using alternative suppliers and service providers,
- Quality and performance improvement programs for suppliers and providers,
- Communication and information sharing between SC partners,
- The use of RFID, mobile devices and track & trace to enhance the transparency,
- Personnel training, shorter work intervals, motivation, relations with labor union, ergonomic analysis of working conditions, reward systems, and social activities,
- Periodic maintenance,
- Insurance,
- New financial tools such as mutual credit transaction and option,
- Mortgage and spot transaction,
- Joint and common traverse processes with industrial partners,
- Establishment of emergency scenarios,
- Business Continuity Management.

All of the tools and methods in SCRM have their own functionality. It is necessary to use a combination of different methods to cope with various risks in SCs.

SCRM strategies may be classified under two different managerial dimensions: internal-operational and inter-organizational (Revilla and Sáenz, 2014). Internal-operational risk management focuses on the management of the risks within the focal organization. Inter-organizational management includes the management of risks cooperatively with other stakeholders, suppliers and customers. Oke and Gopalakrishnan (2009) classified mitigation strategies in two general categories: i) generic strategies that deal with all types of risks, ii) specific strategies that are specific to a particular risk type. Manuj and Mentzer (2008) classified risk management strategies into seven groups: avoidance, postponement, speculation, hedging, control, sharing/transferring, and security. Andersen and Terp (2006) introduced five strategies for risk control; avoidance, prevention, reduction, segregation, and transfer.

Tuncel and Alpan (2010) divided risk management actions into four general categories: i) risk taking, ii) risk mitigation, iii) risk avoidance, and iv) risk transfer. Xia and Chen (2011) mentioned from some of the actions that practitioners may use for dealing with SC risks: separation, transfer, weakening, avoidance and insurance. They also

emphasized the necessity to combine risk management methods with prospective risk managerial factors and organization goals for a good performance.

To cope with disruptions, Chopra and Sodhi (2004) proposed stockpiling inventory that have low holding costs and don't have obsolescence risk; and using redundant suppliers for inventories with high holding costs and high degree of obsolescence. Meade and Sarkis (1998) proposed shared/shifted risk for logistics and listed some of the supporting attributes for the effective management of this principle as follows: creation of standards, improved outsourcing arrangements and capabilities, and supplier customization.

Takata and Yamanaka (2013) focused on the risks associated with the parts of products without identifying suppliers and evaluated the applicability of countermeasures by the bill of material (BOM) based SCRM method. They considered four countermeasures to reduce the risks of part shortages: multiple sourcing, use of replacement parts, redeployment of production sites, and building inventories. Revilla and Sáenz (2014) investigated the universality application of a Supply Chain Disruption Management (SCDM) framework. Their empirical findings show that despite the differences in the sources of SC risks, SC disruption management can be implemented universally. Hallikas and Lintukangas (2016) listed some of the supply risk mitigation activities with their importance according to the results of a survey in Finnish companies. The most important activities are determined as follows: collaboration with suppliers in risk management, multiple sourcing, setting up and enforcing contractual obligations, avoidance of certain suppliers, avoidance of certain geographical areas and use of local domestic suppliers.

Quantitative and qualitative techniques may be used in the risk assessment step of SCRM. Tang (2006) reviewed various quantitative models in SCRM and listed four basic approaches for SCRM: supply management, demand management, product management, and information management. Chan and Wang (2013b) listed some of the quantitative techniques as follows: failure mode and effects analysis (FMEA), probability and impact grids, Monte Carlo simulation, sensitivity analysis, event tree analysis (ETA) and fault tree analysis (FTA).

Various authors have carried out a literature review on SCRM (Tang, 2006; Khan and Burnes, 2007; Ghadge et al., 2012; Olson and Wu, 2010). Ghadge et al. (2012) made a systematic literature review on 120 articles between 2000 and 2010. They tried to identify the developments and outline future research directions in SCRM field. According to their literature review, Lavastre et al. (2012) identified 21 techniques to minimize risk levels. Some of the techniques are safety stocks, multiple sourcing, establishment of emergency scenarios, collaboration and information exchange, and quality and performance improvement programs. They also made an empirical study of 142 general managers and logistics and SC managers in 50 different French companies. The results contain a ranking table for the tools used in SCRM. The most popular SCRM tools are those focusing on continuous improvement (Plan-Do-Check-Act (PDCA), six sigma, etc.). Zhang and Li (2010) reviewed the recent literature on SCRM to discover the limitations of the existing studies. They emphasized the importance of quantitative methods and default correlation in SCRM.

Tang and Musa (2011) reviewed 138 articles between 1995 and the first half of 2008 in order to investigate the research developments in SCRM. They identified major risk issues in material, information and financial flows and categorized the perspectives of risk events under these three headings as qualitative and quantitative solutions. Some of the findings of their literature survey are as follows: i) Main SCRM articles are found in the business/management review journals. ii) The number of quantitative oriented articles have been increased after 2004. However, the number of quantitative models are not sufficient. iii) Most of the studies contain conceptual models, reviews, industrial case studies and interviews.

Most of the studies in the literature focus on mitigating the impacts of risks. Companies should also focus on methods to predict and prevent the risks before occurring. It is hard to predict and quantify the potential losses and disruptions. Therefore, companies have to apply preparation and precaution activities for potential disruptions. Rare risks should also be considered along with frequent risks in the decision making processes. Especially disaster recovery, emergence response and business contingency plans have a high importance for companies (Airmic Technical, 2013). Knemeyer et al. (2009) gave a list of some countermeasures for catastrophic risks and the impacts of these actions. Their list includes relocating facility, buying insurance, increasing the number

of security personnel, etc. Langholtz et al. (2014) gave a list of risks and strategies for the extreme weather events in the bioenergy sector.

The use of modern and high technology decision support systems in SCM is increasing due to technological developments. Giannakis and Louis (2011) developed a framework of a multi-agent based Decision Support System (DSS) for risk management in manufacturing supply chains. Their study contains five software agents; communication, coordination, monitoring, wrapper, and disruption manager agents. In addition, today an increasing number of companies started to use data analysis to reduce the likelihood of SC disruptions (Tsumoto et al., 2007; Dogan, 2011). However, more systematic, responsive, interactive and real time tools and techniques are required for a better SCRM.

3.5. Supply Chain Sustainability and Risk Management

Sustainability is an important concern for organizations and today sustainability efforts have expanded to SC networks (Altuntaş and Türker, 2012). The roots of sustainability concept dates back to a debate that began in the early 1970s about the benefits of economic growth and the preservation of environment and the social structure (AON, 2007). Sustainable development has been defined in many ways. World Commission on Environment and Development defines sustainable development as “development that meets the needs of the present without compromising the ability of future generations to meet their needs” (WCED, 1987). Most of the definitions of sustainability refer to preserving and balancing the triple bottom line of environment, society and economy.

Some trends and developments including environmental awareness of customers, customer demand for eco-friendly products and services, increasing environmental costs and major risk events have led organizations to sustainability (Keeble et al., 2003; Seuring and Müller, 2008). Pressures imposed by governments, customers, competitors and international community force companies to deal with sustainability issues and, balance profitability and sustainability (Seuring and Müller, 2008). Therefore, in recent years, companies have started to pay closer attention to the economic, environmental and social implications of their operations. Companies need to integrate sustainable

strategies into their SCM system and business decisions to improve the performance of their SC.

The combination of sustainability efforts with SCM revealed the concept of Sustainable Supply Chain Management (SSCM) (Er Kara and Oktay Fırat, 2016). SSCM is a SCM strategy that simultaneously considers and manages economic, social and environmental impacts of the SC network to create, protect and increase long-term profitability and value (UN Global Compact, 2010; Srivastava, 2010).

Risk is an important issue that threaten the sustainability of SCs. SC disruptions and vulnerabilities have a huge effect on SC's performance and sustainability. Companies need to integrate their risk management systems into their sustainable business policies and strategies in order to cope with the dynamic and risky business environment. Risk management techniques progress in parallel with the developments in sustainability concerns (Pollard and Stephen, 2008). Although sustainability and risk management have been studied extensively in the literature, only a few authors explicitly examined the relationship between them (Hitchcock and Willard, 2006; Carter and Rogers, 2008; Buddress, 2013; Govindan et al., 2014; Lam and Quinn, 2014).

Er Kara and Oktay Fırat (2016) explained the sustainability and risk management concepts in SCs and discussed their relationship. In a further study, they examined the relationship between sustainability and risk management with a multi-dimensional point of view (Er Kara and Oktay Fırat, 2017a). To the best of our knowledge, it is the first study that examine the relationship between these two concepts with a multidimensional approach. They listed four different approaches:

- i) Sustainability is a new factor that broadens the scope of risk management.
- ii) Sustainability practices may decrease risks.
- iii) Risk management is a tool for sustainable development.
- iv) Sustainability efforts may also lead to some risks such as fraud, misuse, greenwashing, false claims and wrong perceptions (Hitchcock and Willard, 2006; PwC, 2011).

Carter and Rogers (2008) developed a SSCM framework that is based on the triple bottom line and four supporting facets of sustainability: risk management, transparency,

strategy, and culture. Figure 3.13 represents the proposed SSCM framework with some key issues under the proposed supporting facets.

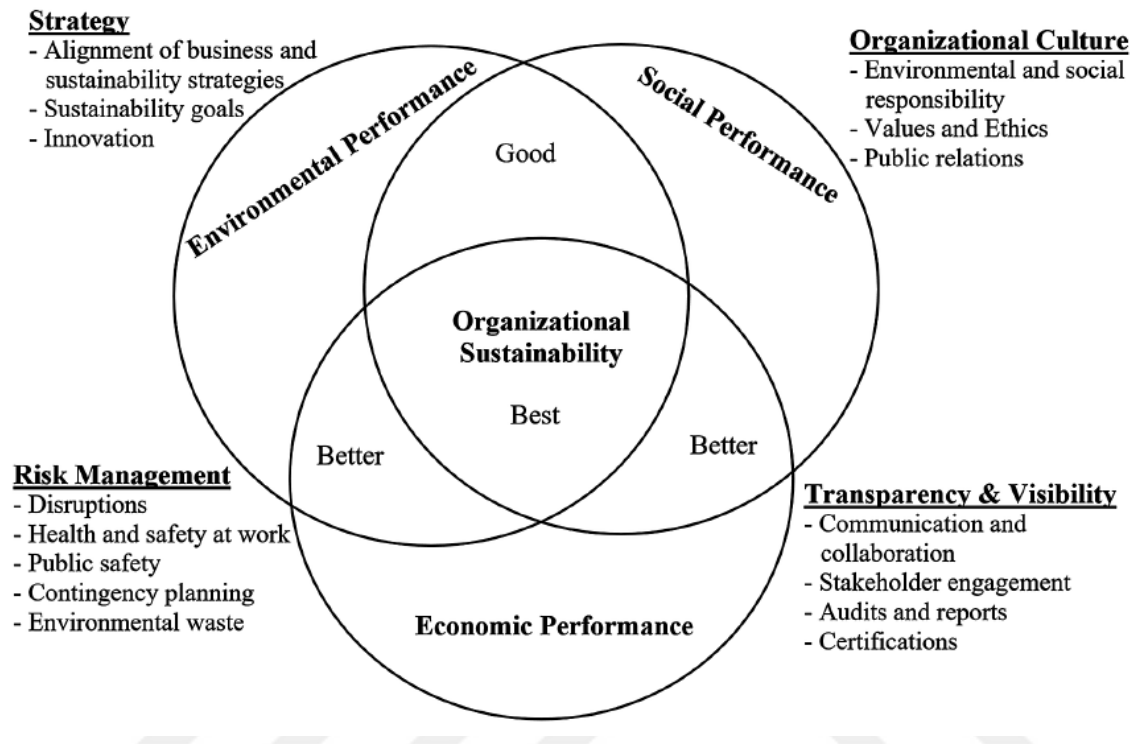


Figure 3.13. Supply chain sustainability (Adapted from Carter and Rogers, 2008)

Seuring and Müller (2008) proposed two distinct strategies within their conceptual framework for SSCM: i) supplier management for risks and performance, and ii) SCM for sustainable products. Altuntaş and Türker (2012) developed Seuring and Müller's (2008) theoretical approach by adding some of the frequently discussed issues in the literature; e.g. supplier development, communication with suppliers, Environment Management System, risk avoidance and performance improvement. Altuntaş and Türker (2012) also proposed to evaluate suppliers in terms of risk in order to manage supplier-related risks and enhance the sustainability of SCs.

4. DATA MINING AND SUPPLY CHAIN RISK MANAGEMENT

There are a limited number of academic studies related with the use DM techniques in SCRM. Hence, we expanded the scope of this part to cover Business Intelligence (BI) area and the use of BI tools and techniques in managing SCs and their risks. This chapter starts with an introduction to BI and DM concepts. Then a literature review is presented on the researches associated with data analysis and management both in the SCM and SCRM fields. Then some risk related data and indicators that are used by enterprises are explained briefly.

The case study of the proposed model focus on the application of a cluster analysis in evaluating suppliers based on their risk profile. Therefore, the last section of this chapter includes supplier evaluation and selection process, traditional, emerging and risk-related criteria considered in this process and clustering approaches in supplier evaluation and selection literature.

4.1. Business Intelligence and Data Mining

Today companies save billions of dollars by using BI solutions for their daily operations. BI has emerged from DSS that is extensively used to support business planners and decision makers in complex decision-making and problem solving processes. Hans Peter Luhn, an IBM researcher, first used the term “business intelligence” in 1958 (Luhn, 1958). BI contains the databases, tools, techniques, processes, functions and technologies for the transformation of raw data into meaningful and useful information for business analysis purposes (Biere, 2003). BI includes different functions and software for Extract, Transform and Load (ETL), data warehousing, Online Analytical Process (OLAP), statistical analysis, DM, prediction, visualization, etc. (Sahay and Ranjan, 2008). Stefanovic et al. (2006) examined the development stages of BI in six steps: justification, planning, business analysis, design, construction and deployment. Business analysis step includes data analysis, application prototyping and metadata repository analysis. Design step covers the design and development of database, metadata repository and ETL process. Application development, DM and ETL development are performed in the construction phase.

BI is an umbrella term describing different concepts and methods to improve business decision making and business performance. Sahay and Ranjan (2008) defines BI as a combination of data warehousing and DSSs. Sherman (2015) represented some key terms related with Data Integration (DI), Data Warehousing (DW) and BI. The categorization of Sherman (2015) is adapted and given in Figure 4.1. BI provides the access of business users to the valuable and competitive information.

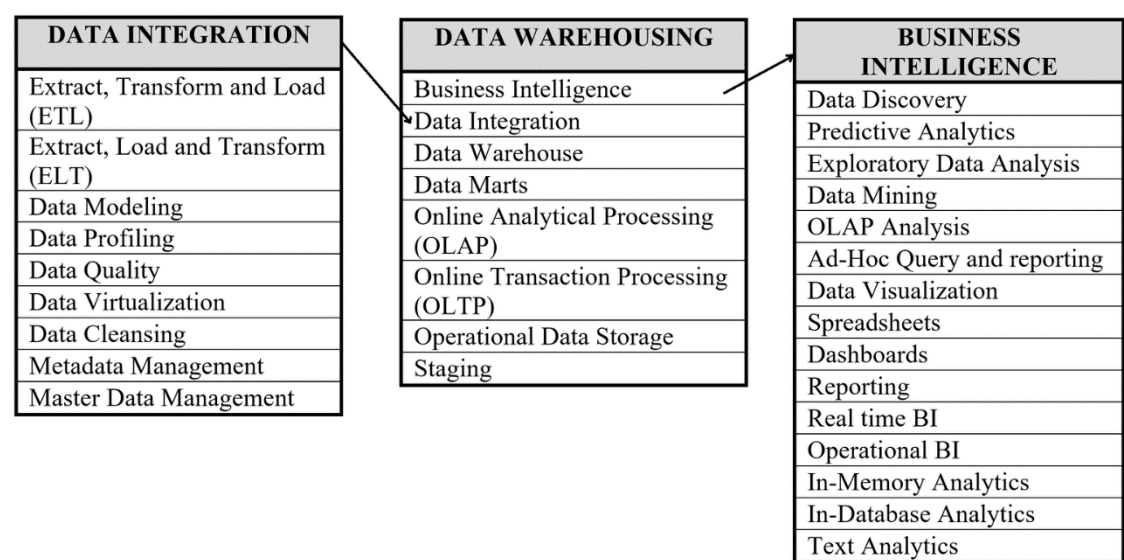


Figure 4.1. Categorizing Business Intelligence, Data Warehousing and Data Integration terminology (adapted from Sherman, 2015)

Data warehousing emerged in the late 1980s to provide the data infrastructure for DSSs (Anderson-Lehman et al., 2004). A data warehouse combines data from multiple sources of an organization into a single and central repository in order to support decision-making process (Dunham, 2003; Kulkarni and Bakal, 2014). Data warehouses are mainly used for analysis and reporting. A data warehouse gathers and integrates data from numerous enterprise records and external sources (Sahay and Ranjan, 2008). The data of an organization are stored in operational systems. A summary of this data are transferred by ETL process and organized in a data warehouse in a relational form (Prenhall, 2017).

Data warehouses are different from operational databases. Some of the differences may be listed as follows (Velicanu and Matei, 2007; Wang, 2008):

- i) A data warehouse is subject oriented, but an operational database is process or application oriented.
- ii) While data warehousing is an enterprise wide project, operational databases are developed by different departments in different ways.
- iii) While data warehouses generally contain historical and static data, operational databases include current/near current data extracted from operational systems and the data is updated periodically.

BI includes DSS, executive information systems (EIS), DM and OLAP (Anderson-Lehman et al., 2004; Dunham, 2003). OLAP provides multidimensional view of data (Sahay and Ranjan, 2008).

DM may be seen as a bridge between BI and Knowledge Management (Ranjan and Bhatnagar, 2011). DM helps to gain hidden and unknown information from databases and plays a critical role in providing a BI environment (Ranjan and Bhatnagar, 2011). DM is an important part of Knowledge Discovery in Databases (KDD) process. KDD is the process of finding hidden and useful information and patterns in large and separate data repositories and involves many different steps such as selection, preprocessing, transformations, DM, and interpretation/post-processing (Dunham, 2003). DM is the use of algorithms to discover these information and patterns derived by the KDD process (Tan et al., 2006; Dunham, 2003; Oktay Firat, 2012). DM uses data warehouses or databases for analysis and reporting. DM is an interdisciplinary field and adapts techniques from many domains such as statistics, data and database management, machine learning, artificial intelligence and data visualization (Han et al., 2012; Feelders et al., 2000). It uses advanced techniques and complex algorithms. DM can be seen as an automatic or semi-automatic analysis of large data sets.

Lee and Siau (2001) listed three main steps of DM: i) preparation of the data, ii) reduction of the data, and iii) searching for valuable information. Feelders et al. (2000) listed the main stages of a DM process as follows: i) Formulation of the problem, ii) Identification of the background knowledge, iii) Data selection, iv) Pre-processing of data, v) Analysis and interpretation, and vi) Reporting and use. Giudici and Figini (2009) categorized the main phases of a DM process as in the following: i) Definition of the aims of the analysis; ii) Selection, organization and pre-treatment of the data; iii)

Exploratory analysis of the data and data transformation process; iv) Specification of the descriptive and predictive methods that will be used in the analysis of the data; v) Analysis of the data by using the selected methods; vi) Selection of the final model after evaluating and comparing different methods; and vii) Interpretation of the model and using it in the decision making process of the company.

The following issues should be examined in order to develop robust data models (Pyle, 1999);

- Source of data
- Quantity of data
- Quality of data

Data quality is an important concern in DM and need to be assessed before analysis. Data quality refers to the degree to which data meet a purpose or a need (Kulkarni and Bakal, 2014). The quality of the knowledge extracted from the DM algorithm and decision making highly depends on the quality of the data. Data entry, storage, transmission and management processes affect the data quality. The problems in data quality are listed in the following (Pyle, 1999; Jermyn et al., 1999):

- i) Missing data: It occurs when data is not present.
- ii) Empty values: It is hard to differentiate missing and empty values hence; they should be treated similar with missing values.
- iii) Noisy data: It refers to the data that is present but incorrect. The detection of erroneous data is generally very difficult.
- iv) Duplicated data: It refers to the repeated records with different values or repeated entry of the same value.
- v) Inconsistent data: Inconsistency occurs when similar data is recorded in different formats in different files.
- vi) Heterogeneities: The meaning of data may be different in different systems. Heterogeneities occur when data from such systems are combined.

The raw data generally needs to be preprocessed before analysis. Data preprocessing includes data cleaning, data integration, data reduction and data transformation steps (Dunham, 2003; Kulkarni and Bakal, 2014). Data cleaning (cleansing) deals with detecting wrong, missing, empty and inconsistent data and outliers. The noise in the

data set is removed and missing data is estimated or supplied in order to improve the quality of the data. Rahm and Do (2000) provide an overview of the data quality problems and solutions that are addressed by data cleaning. Statistics may be used to detect outliers, estimate noise and estimate missing data (Lee and Siau, 2001).

Data integration involves combining data from multiple heterogeneous sources and provide a unified view of the data (Bhardwaj, 2011). Data reduction includes the reduction of the number of values, attributes or tuples. The number of values may be reduced by grouping them into intervals, clustering, aggregation or generalization. Data reduction includes the following strategies (Bhardwaj, 2011):

- i) Data cube aggregation
- ii) Dimensionality reduction
- iii) Data compression (reduction of the size of the data set)
- iv) Numerosity reduction
- v) Discretization and concept hierarchy generation (values are replaced by ranges or higher conceptual levels)

Principle Component Analysis (PCA) is a very popular technique in dimensionality reduction (Tan et al., 2006). PCA is a mathematical procedure that aims to reduce the number of variables without losing the information in the data set.

Data also should be converted into a single appropriate form before modeling. This process is called data transformation and involves normalization, smoothing, aggregation, attribute construction, discretization, and generalization (Bhardwaj, 2011). The most common data transformation technique is normalization that aims to scale data within a specific range. Categorical values should also be numerated in most of the modeling techniques (See Chapter 6 in Pyle, 1999).

Most of the DM tools are related with building models that connect a set of inputs to a target or output; e.g. regression, decision tree, association rules, neural network (NN), etc. (Berry and Linoff, 2004). Generally DM tasks can be classified as descriptive and predictive (Dunham, 2003). Predictive analysis contains the following tasks;

- i) Classification,
- ii) Regression,
- iii) Time series analysis,

- iv) Prediction.

Descriptive DM tasks include;

- i) Summarization,
- ii) Clustering
- iii) Association rules,
- iv) Sequence discovery.

Classification is the separation of the observations into predetermined number of classes (Dunham, 2003). Classification aims to generate a model that can be applied to unclassified items by using past data (Jha and Hui, 2006). Different from classification prediction focus on a future state and outputs. Prediction is one of the most common tasks of DM (Jha and Hui, 2006). Prediction uses past data to predict future (Berry and Linoff, 2004). Regression is the oldest and most used statistical technique in DM field (Refaat, 2007). Regression develops a mathematical model that fits a numerical dataset. Summarization refers to the methods that are used to find a brief description of a dataset (Jha and Hui, 2006).

Association analysis is used to discover interesting relationships and frequent patterns hidden in data sets (Tan et al., 2006). The discovered relationships can be represented in the form of association rules that are primarily used for cross selling (Berry and Linoff, 2004). Association rules support the decision making process. Anomaly detection is identifying the observations that are different from the rest of the data (Tan et al., 2006). Sequence discovery aims identifying sequential patterns in the data based on time (Dunham, 2003).

Clustering (Cluster analysis) is a component of exploratory data analysis. Clustering tries to group the observations into subsets based on the similarity in their characteristics and form homogenous subgroups (Berry and Linoff, 2004; Tan et al., 2006). The difference between classification and clustering is that the groups are defined by the data set in clustering (Hair et al., 2006). However, in classification groups are pre-defined. The groups in clustering are called clusters. Clustering techniques are very useful in detecting similarities and dissimilarities between numerous data sets (Khaleie et al., 2012). Clustering is performed depending on the similarities in

the data on different predetermined characteristics/attributes. Selection of similarity measure is a very important decision point in clustering. Similarity is usually measured by distance measures. The most common similarity measures in clustering are distance measures such as Euclidean distance, Manhattan distance, Chebychev distance, etc. (Hair et al., 2006).

The most common distinction among clustering methods is done according to the set of clusters to be hierarchical or partitional (Tan et al., 2006; Heidarzade et al., 2016). Partitional clustering algorithms divide the given data set into non-overlapping subsets (clusters) that each object belongs to exactly one subset. All clusters are found simultaneously. Hierarchical clustering algorithms generate nested clusters organized as a hierarchical tree. There are two basic types of hierarchical clustering approaches (Hair et al., 2006): i) Agglomerative methods: Each observation is assigned to its own cluster at the beginning; ii) Divisive methods: All observations are assigned in a single cluster and then successively divided until each cluster has a single member.

The interpretation of the generated clusters is a very important step of a clustering study (Berry and Linoff, 2004). Generally, a domain expert is needed to comment on the generated clusters (Dunham, 2003). Clustering algorithms should also be supported by data visualization techniques. Visualization transforms data in a more visible form (SAS, 2014). While exploring data, data visualization techniques can be used to display/interpret the information in a graphic or tabular format for better analysis and reporting (Tan et al., 2006). Graphs and tables enhance the understanding of the data. The relationships between different items and trends become more obvious.

There is a myriad of clustering algorithms in the literature. Jain (2010) summarized well-known clustering methods. One of the most popular clustering algorithms is k-means clustering (Berry and Linoff, 2004). K-means algorithm clusters observations into k groups where k is an input parameter. It assigns observations into clusters based on their distance to the mean of the cluster. The means of the clusters are computed in each iteration.

In business life, clustering has been used in various areas. One of the most common applications is grouping customers with similar features to create efficient marketing

campaigns for each group (Dunham, 2003; Anil et al., 1997). Another example is the cluster analysis for portfolio selection (Karabayır and Doğanay, 2010).

DM includes various types of methods and techniques to perform different tasks (Liao et al., 2012). In addition, there are some approaches that integrate different algorithms especially in hybrid systems. Table 4.1 represents the basic DM tasks and gives some of the general methods used for these tasks. Artificial Intelligence techniques including NN and fuzzy sets are commonly used in DM (Lee and Siau, 2001).

Table 4.1. Some common DM methods

DM Tasks	Some Example Methods
Classification (Tan et al., 2006; Gupta, 2011; Dunham, 2003)	Decision Tree, Bayesian Method, Rule Based Classification, NN, Support Vector Machine, Fuzzy Sets, etc.
Clustering (Berry and Linoff, 2004; Tan et al., 2006; Jain, 2010; Gupta, 2011)	K-means Algorithm and its Extensions, Agglomerative Hierarchical Clustering, Ward's Method, etc.
Association Analysis (Tan et al., 2006; Agrawal and Srikant, 1994)	Apriori, FP-Growth, etc.
Prediction and Regression (Berry and Linoff, 2004)	Decision Tree, Association Rules, NN, etc.
Data Preprocessing (Han et al., 2012; Tan et al., 2006; Han et al., 2012)	Data Cleaning, Data Integration, Data Reduction, Data Transformation and Data Discretization, Feature Subset Selection, Sampling, Dimensionality Reduction
Data Visualization (Tan et al., 2006)	Pie Chart, Histograms, Stem and Leaf Plots, Box Plots, Scatter Plots, Matrices, etc.
Summarization (Han et al., 2012)	
Anomaly Detection (Tan et al., 2006)	Proximity Based Outlier Detection, Density Based Outlier Detection, Clustering Based Techniques, etc.

DM literature is rich of studies concerning various different applications in different fields such as credit card business, hospital information systems, etc. Liao et al. (2012) surveyed and classified 216 articles concerning DM techniques and their applications,

from 2000 to 2011. DM has many successful applications in different areas. Gupta (2011) presented different case studies for different DM algorithms. Giudici and Figini (2009) presented DM case studies from real industry projects. The book of Berry and Linoff (2004) covers DM applications in marketing and customer relationship management. DM algorithms are often used as a combination of different techniques.

Today, various database vendors offer DM products incorporated in their platforms such as SPSS of IBM, SAS, DM Suite of Oracle and Microsoft SQL Server. The success of DM depends on the appropriate choice and combination of the techniques for a given problem.

4.2. Business Intelligence and Data Mining in Managing Supply Chains and Their Risks

Nowadays SCs are highly complex, integrated and geographically dispersed systems. Logistics and SC management systems are developing due to highly competitive environment, technological innovations, increased globalization, collaboration, cooperation and communication between SC members, integration of SC operations, trends in customer expectations and growing e-business systems. These developments and the advances in information and communication technologies increase the information loads in SCs. In addition to goods, SCs contain the generation, transfer and use of huge amounts of data. Collection, storage, management and utilization of data has been one of the major and strategically important activities for enterprises today (Stefanovic et al., 2006). Companies have to deal with huge amounts of different and distributed data sources in order to take right decisions and handle with the risks in SCs (Marra et al., 2012; Lam and Quinn, 2014; Wu et al., 2014). The growth in the implementation of modern information technology has increased the amount of data generated, stored and transferred within SCs. The data may be about costs, revenue, production, inventory, orders, sales, transportation, customer feedback, etc. Today there are cheap and efficient methods to collect, store and transfer data, but data means nothing without bringing it to a meaningful knowledge. Data and knowledge management has a high importance to cope with the complex and high volume data sources of SCs and gain competitive advantage (Marra et al., 2012).

Data access, data management and data monitoring are critical activities for managing an enterprise effectively (Sahay and Ranjan, 2008). The success of companies relies on the effectiveness of the use of data emerged from their SC operations (Meade and Sarkis, 1998; Solomon et al., 2012). Advanced computing techniques and models are required to work on these data efficiently. BI and DM are essential cornerstones in business analytics and successful SCM systems (Ranjan and Bhatnagar, 2011). Today a lot of companies use BI tools and techniques in SCM to make efficient and timely decisions (Manhattan Associates, 2008). There are various studies in the literature on the use of BI paradigm in SCs (Rabelo and Pereira-Klen, 2002; Anderson-Lehman et al., 2004; Sahay and Ranjan, 2008). DM may be very efficient in various activities in SCs from lead time estimation and quality improvement to customer profiling (Bounsaythip and Rinta-Runsala, 2001; Köksal et al., 2011). DM is extensively used for knowledge management (Ghadge et al., 2012).

The advances in computing and communication systems have resulted in increased collaboration between the members of SCs. Therefore, it requires monitoring and analyzing different distributed sources of high volume data. DM technologies designed for distributed applications can be very efficient in the distributed computing environments.

Real time BI is a critical component to enhance the effectiveness and efficiency of SC analytics and risk management activities. Today, real time data analytics, real time processing, real time warehousing and real time transfer concepts gain increasing attention in business life. Sahay and Ranjan (2008) analyzed and described the role of real time BI in SC analytics. Anderson-Lehman et al. (2004) introduced real-time BI and data warehousing used in Continental Airlines. A data warehousing team including 15 people is responsible for the development, management and maintenance of the warehouse and data modeling. Real time data warehousing and BI helped the organization to improve its industry position and increase revenue and cost savings. Web-based tools may be used to support risk management activities. Fugini et al. (2016) proposed a web-based system for collaboration and cooperation in risk management.

Despite the industrial interest in BI in SCM and SCRM, the academic literature is not rich enough on the adaption of these tools and techniques in SCRM, and there is a

research gap in this area (Petrini and Pozzebon, 2009; Lee and Kulkarni, 2011; Wu et al., 2014). Today a new concept, “Risk Intelligence (RI)”, is emerged with the developments of the techniques that are used for the analysis and management of risk data. Apgar (2006) defines risk intelligence as “an individual’s or an organization’s ability to weigh risks effectively”. Lee and Kulkarni (2011) introduced risk intelligence as an effective risk management method and examined the application of BI in managing corporate risks. RI provides a more proactive risk management approach by predicting potential risks before their occurrence. Haksöz (2013) introduced the risk intelligent SC concept and presented examples from some Turkish companies in his book.

Liu et al. (2013) studied on the use of BI and analytics for improving SCRM. They stated that companies could detect, prevent or mitigate an incident and its effects by having the right information at the right moment. In a latter study, Liu et al. (2014) examined the applications of BI technologies in management control and risk management. Zouzelkova (2011) proposed OLAP technology as a suitable tool in SCRM and SCM, and discussed advantages and disadvantages of OLAP in SCRM. According to Zouzelkova (2011), OLAP enables to make analysis on different levels of company structure and in different time ranges with its multidimensional concept. Figure 4.2 represents the components in the implementation of OLAP in SCRM and the connection between these components (Zouzelkova, 2011). There is a separated warehouse that is connected with other databases in the company.

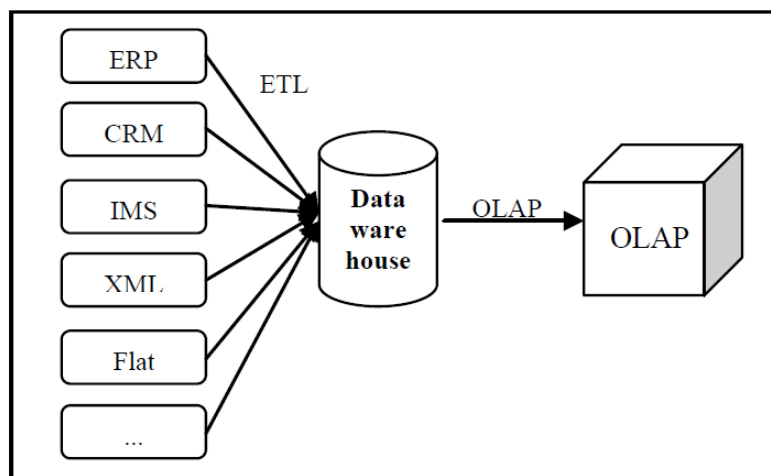


Figure 4.2. OLAP implementation in SCRM (Zouzelkova, 2011)

Graphical visualization of SC networks can provide an overview of the network structure and make the structure, flows, relationships and data presentations more visible. Thus, significant insights may be obtained about possible risks and their sources. Basole and Bellamy (2014) demonstrated the importance of visual decision support for supply network risk assessment and gave visualization examples from the electronics industry. Figure 4.3 (a) represents their conceptual model of risk visualization approach. Figure 4.3 (b) shows the supply network that includes the topological importance and risk level information. They also gave a table containing several risk areas and a set of representative measures for each area.

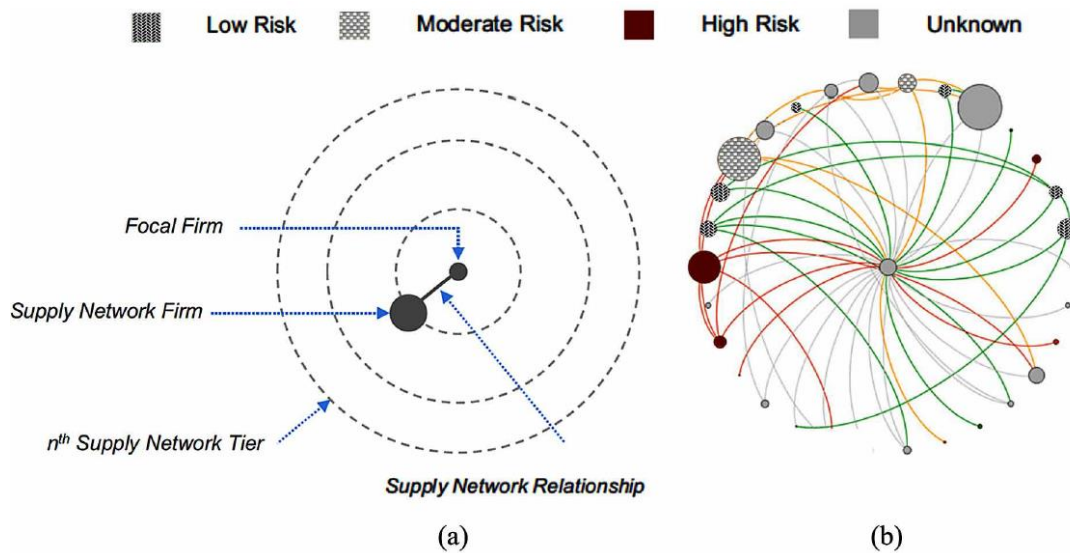


Figure 4.3. A conceptual model of risk visualization in supply networks (Basole and Bellamy, 2014)

In Ericsson's risk management approach, suppliers' position for different risks and their predicted development are summarized in spider-web diagrams to monitor improvements (Norrman and Jansson, 2004). An example spider-web diagram is given in Figure 4.4. Goh et al. (2013) developed a multi-hierarchical modular SC visualization platform, RiskVis, to improve the performance of SCRM. This platform provides the opportunity for real-time risk data collection, monitoring and risk alerting. It also utilizes from DM tools.

According to Neef (2005), a company cannot manage its risk successfully without managing its knowledge. Knowledge Management is more focused on the use of

technological infrastructure then BI (Ranjan and Bhatnagar, 2011). Few researchers studied on the application of knowledge management in SCRM. Neef (2005) studied on the integration of knowledge and risk management systems. He also explained some of the knowledge management techniques that are used in the knowledge and risk management processes; e.g. knowledge mapping, creating a culture for knowledge sharing and performance reporting. Similarly, Guo (2011) studied on the integration of knowledge management into risk management process and proposed a knowledge-oriented SCRM model.

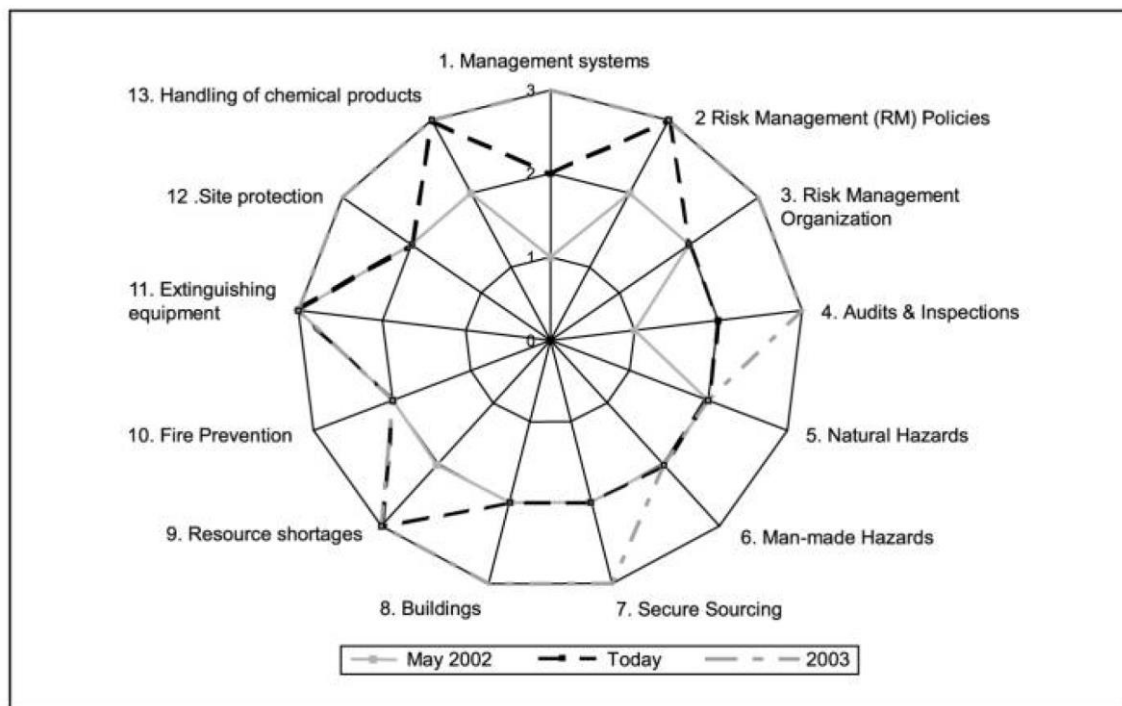


Figure 4.4. An example Spider-web diagram for supplier risk (Norrman and Jansson, 2004)

He and Song (2009) considered that SC knowledge management researches focus on knowledge types, management, sharing, transfer and their effects on SC's performance. They emphasized the need to analyze enterprises' data to decrease SC risks and have proposed a knowledge-based SCRM framework. Their model consists of four modules: basic database, knowledge database management, SC risk early warning and risk management strategies modules. Finally, they defined three simple association rules applications for SC partners' attributes. Ye et al. (2012) proposed a SC risk control system based on a knowledge management system. Risk management constitutes of

knowledge definition, knowledge organization, knowledge retrieval and knowledge acquisition modules. Two-dimension grey clustering analysis was used to evaluate the knowledge management level of the risk control system (Gao and Zheng, 2012).

Kayis and Karningsih (2012) developed knowledge-based SC risk identification tool that aims to assist decision makers in identifying risks and their inter-relationships in SCs. They represented risk knowledge in a rule-based structure for linking different attributes of risks. Solomon et al. (2012) stated that the information and communication technologies such as the knowledge and data discovery techniques and automated risk management frameworks became vital for success in today's knowledge driven business environment. They focused on how to effectively use knowledge management structures for SCRM and proposed a risk and knowledge management framework. The knowledge management framework of their model is given in Figure 4.5. The risk knowledge base stores the risks for which a solution has been applied previously. For further research, they addressed to integrate the proposed framework in an agent based decision support system for SCRM.

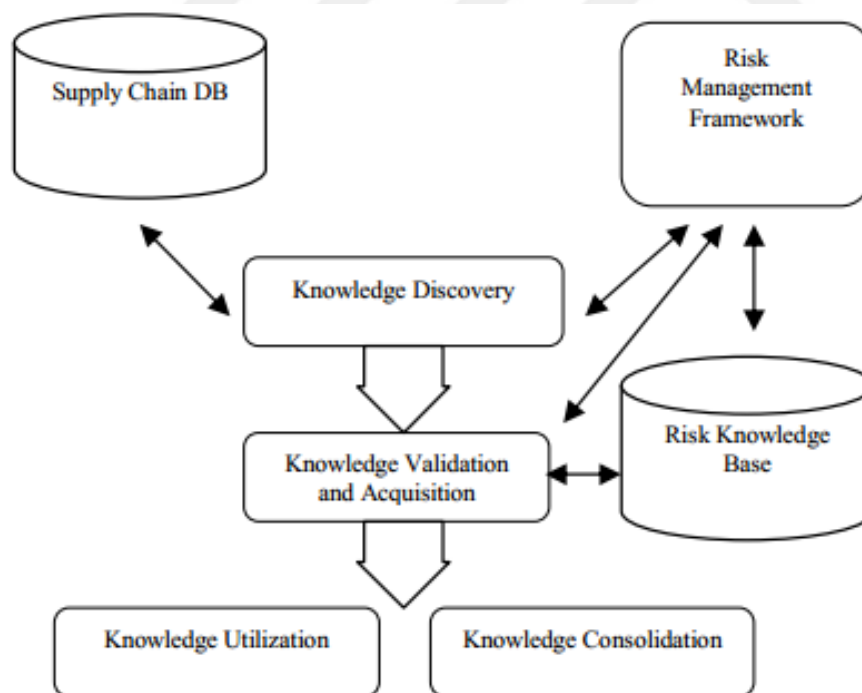


Figure 4.5. Risk and knowledge management frameworks (Solomon et al., 2012)

Alhawari et al. (2012) studied on the use of Knowledge Management processes in Risk Management and proposed a conceptual framework, called Knowledge-Based Risk Management. Their model includes a knowledge-based risk repository that integrates knowledge management and risk management databases for risk analysis.

There are only a few studies in the literature related with the application of DM algorithms in SCRM. The use of DM in SCRM is still in its early stage. The existing literature have been done in the recent years (Thun and Hoenig, 2011; Ye et al., 2012; Le et al., 2013). Some of the application areas of DM in risk management are; quality control, competitive analysis, identification of risky customers, fraud detection, etc. (Baykal, 2006). DM techniques are frequently used in Customer Relationship Management (CRM) and customer risk analysis especially in the insurance and banking industries. Lai et al. (2007) focused on identifying high-risk customers in Customer Relationship Management and used Support Vector Machine. Jha and Hui (2006) presented different examples of DM tasks that are used in risk analysis and marketing in real-life. Examples include classification of customers into different risk groups, predicting customers' risk value for credit granting, association analysis for market basket analysis to assist in risk analysis. Dogan (2011) examined the role of data warehouses and DM in risk analysis to detect unreported activities of taxpayers and tax fraud.

Rashid (2014) proposed to use DM to evaluate SC performance and risks in procurement process, but the application is very limited. Yin et al. (2015) proposed a network connectivity embedded k-means clustering approach to identify high-risk zones. The proposed approach helps to decrease the complexity of a wide SC network. Thun and Hoenig (2011) made a survey to 67 manufacturing plants in German automotive industry in order to investigate vulnerability of SCs and sources of SC risks. They applied Ward's method to cluster the companies with preventive, reactive or no SCRM. Constructed three clusters were compared according to performance criteria and preventive SCRM showed a better performance. Topak (2010) applied two-step Cluster Analysis to calculate the business risk, financial risk and the total risk of 129 manufacturing firms listed in the Istanbul Stock Exchange. He used financial ratios derived from the quarterly financial statements.

Le et al. (2013) focused on association rule hiding to avoid risks caused by sensitive knowledge leakage during knowledge share in retail SC. Association rule hiding is an emerging area of DM that transforms an original database into a released database in which sensitive association rules cannot be discovered (Le et al., 2013). They proposed a heuristic algorithm to hide a set of association rules from a released database before sharing it.

There is a need for empirical studies for the analysis of SC risks and risk management methods in the SCRM area (Thun and Hoenig, 2011). According to the literature review of Tang and Musa (2011), the need for integrated approaches in SCRM has been growing and SCRM needs an integration of knowledge from multiple researches disciplinary.

Nowadays, the scale, volume, scope and velocity of SC data is accelerating. Therefore, some big companies started to pay attention on embedding big data analytics into their SCM system. SC data have the properties of big data that is described by five Vs: variety, velocity, volume, verification, and value (Oktay Firat, 2015). There are a limited number of researches on the use of big data analytics in SCM and this area is in its early stages. We refer to Addo-Tenkorang and Helo (2016) for a literature review on big data and its applications in operations or SC management.

4.3. Risk-Related Data and Indicators

Companies need to measure and evaluate both the performance of their activities and the risks for an efficient SCM. Gunasekaran et al. (2004) presented a framework for performance measures and metrics in SCM in the context of plan, source, make/assemble and delivery/customer activities in SCs and classified these metrics at strategic, tactical and operational levels. Bhagwat and Sharma (2007) reviewed different SCM performance metrics and applied four perspectives of balance scorecard to evaluate these metrics. Some of these performance metrics are given in the following: i) Financial perspective: e.g. net profit, rate of return on investment, cost/operation hour; ii) Customer perspective: perceived value of product, range of products and services, order lead time, delivery lead time, quality of products; iii) Internal business perspective: Total SC cycle time, accuracy of forecasting, product development cycle time, capacity utilization, total inventory cost; iv) Innovation and learning perspective:

Supplier ability to respond to quality problems, order entry methods, buyer-supplier partnership level.

SC performance measurement and metrics have gained much attention of academic researchers and practitioners (Gunasekaran et al., 2004), but the awareness on the criticality of risk indicators is quite new (Sankey and Chapelle, 2016). A risk indicator is a metric that gives information about a risk (Scarlat et al., 2012). Risk indicators are measurements, statistics or parameters of risk drivers and represent the exposure to a risk factor over time (IOR, 2010; MS, 2014; Sankey and Chapelle, 2016). Risk indicators may be used to identify risks, assess risks, track emerging risk trends, and detect new risks. Risk indicators provide the early indication of risks and hence they are necessary to determine and prevent potential disruptions. Risk indicators have to address risks instead of events (Chapelle, 2013). There are a myriad of indicators that can be used to measure and track different types of risks (Opsdog, 2017). Identification and collection of risk indicator data is critical for the success of SCRM. Risk metrics should be determined carefully. There are hundreds of risk indicators. Risk indicators should be quantifiable. Indicators are generally measured as amounts, percentages, ratios and time duration (Mouatassim and Ibenrissoul, 2015; Andersen et al., 2016). Risk indicators help to measure the level of risk exposures, monitor the changes in risk factors and make better decisions for risk management. A metric is called a risk indicator if it has the following attributes (IOR, 2010): i) It measures the level of exposure to a determined risk(s), ii) It measures the effectiveness and performance of a risk management action that is performed to reduce the exposure to a risk, and iii) The value of the indicator changes depending on the level of risk exposure. The characteristics of a good risk indicator can be listed as follows (IOR, 2010; Andersen et al., 2016): relevant, measurable (quantifiable), predictive, easy to monitor, auditable, and comparable. According to Scarlat et al. (2012), risk indicators should have the following properties: robust, reliable, consistent, easy to collect, and continuous. Chapelle (2013) classified risk indicators as follows:

- i) Exposure indicators: They represent the level of exposure to risks.
- ii) Stress indicators: They track the overuse of resources including human and machines.
- iii) Causal indicators: They measure the drivers of key risks.

- iv) Failure indicators: They are used to detect poor performance factors that lead to risks.

The risk indicators that have a critical importance for the risk management process are called key risk indicators (Scarlat et al., 2012). Key risk indicators are measurable metrics that give information about risk exposures, losses, unfavorable events or other problems (Davies et al., 2006). Key risk indicators help to discover risk exposure, trends, patterns and interdependencies between different risk factors (Matruglio and Tymmons, 2014). Key risk indicators can also be used to measure the effectiveness of risk management activities (MS, 2014). Operational Risk & Regulation and Protiviti (2014) made a survey with 229 operational risk professionals (Protiviti, 2014; Chapelle, 2015). According to their results, key risk indicators are one of the most important components of operational risk profile reports and presentations. 39% of the respondents declared that they have used more than 20 key risk indicators in their organization. The percentage of respondents that do not utilize key risk indicators is only 14%. Operational Risk Sound Practice Guidance Report of the Institute of Operational Risk includes a table that represents different operational risk events and associated applicable key risk indicators in different sectors (IOR, 2010).

Mouatassim and Ibenrissoul (2015) classified key risk indicators into two classes depending on the calculation time: i) key risk indicators of exposure that are calculated before the occurrence of risks, and ii) key risk indicators of prove risk that are calculated after the occurrence of the risk to identify risk mitigation strategies. Matruglio and Tymmons (2014) gave examples to key risk indicators including product segment complaints, sales revenue, cancelled services, delayed services, rainfall forecasts, etc. Guertler and Spinler (2015) specifically focused on supply risk indicators. They gave a comprehensive list of supply risks and associated key risk indicators including; political stability, exchange rate volatility in the supplier's location, unavailability of product knowhow, availability and continuity of contact persons, etc. Similarly, Entchelmeier et al. (2006) gave examples to supply risk indicators. Some of these indicators are number of contract violations of the suppliers, degree of supplier's delivery reliability, status of payment history, country risk indicators, etc.

Scarlat et al. (2012) examined the use of risk indicators and metrics in SCRM. They also explained the difference between key performance indicators and key risk indicators. Key performance indicators specifically consider historical performance of the company and focus on the achievement of business goals. However, key risk indicators focus on real time data and the threats that affect the realization of these targets. According to Davies et al. (2006), this terminology is dependent on the user's perspective. As an example, a key performance indicator in a company may be a risk indicator in another company. According to Chapelle (2013), failed key performance indicators can be used as indicators of key risks. In his book, Marr (2012) explained 75 key performance indicators that every manager should know. Some of these indicators are; revenue growth rate, return on investment, customer complaints, energy consumption, product recycling rate, etc. Similarly, according to Scandizzo (2005), performance indicators give information about the likelihood of an operational failure because these indicators are related with process outputs. Key performance indicators help to identify weaknesses in SCs (La Londe, 2016).

Davies et al. (2006) examined the identification, selection, implementation, monitoring and reporting of key risk indicators. They gave detailed explanations about these steps. Some of the key risk indicators that are mentioned in their study are; number of customer complaints, process error rate, cost of rework, staff turnover, etc. Chapelle (2015) proposed a six-step approach to establish preventive key risk indicators: i) identification of the key risks, ii) understanding the main driving forces of these risks, iii) examining existing metrics (failed key performance indicators and failed key control indicators), iv) identification of the gaps for key risk indicators, v) design of the key risk indicators (data collection and frequency, reporting details, etc.), vi) validation. Andersen et al. (2016) proposed a systematical model for the identification and assessment of key risk indicators using causal analysis and Bayesian Networks for operational risk in financial organizations. Mouatassim and Ibenrissoul (2015) gave a table representing some risks, their causes, associated key risk indicators, and key risk indicator responsible. Some of the risk indicators are absenteeism rate of the staff, number of work-related accidents, inventory turnover, rate of bad loans, and number of IT system failures. They also proposed a methodology for the implementation of a key risk indicator system for operational risks. A key risk indicator system brings the

following advantages for the company (Mouatassim and Ibenrissoul, 2015): i) provide the early and quick detection of risk events, ii) enhance the efficiency of the risk management process, iii) help to react to risk events immediately, and iv) decrease operational losses.

4.4. Clustering and Risk Criteria Approaches in Supplier Evaluation and Selection

The case study of this thesis focus on supplier related risks and includes the clustering of suppliers based on their risk profile. The results of the cluster analysis is used to improve supplier evaluation and selection process, and mitigate supplier related risks. Hence, this section starts with an introduction to supplier evaluation and selection problem. Then, it presents a literature review on supply risk issues and, clustering and segmentation approaches in this field.

4.4.1. Supplier Evaluation and Selection Problem

Today competitions are between SCs rather than companies. The performance or disruption of a member of a SC affects the other members in the network. Especially suppliers have a critical importance for SCs. Procurement and purchasing are vital functions that have strategical importance for the success of an organization. Supplier evaluation and selection is a critical and strategic process for developing a competitive and sustainable SC. It has a direct impact on the performance of organizations and the SC. Purchasing activities constitutes an important part of total production cost. Generally, a company spends almost 60% of its total sales on purchasing raw materials, assemblies, components, parts, etc. (Hamdi et al., 2015). In recent years, supplier evaluation and selection problem has gained increasing attention due to globalization, dependency on suppliers, outsourcing and off shoring. Its importance increases especially when a company searches for new markets and tries to develop a new supplier base (Rezaei et al., 2016).

Supplier evaluation and selection is a complex, risky and hard multi-criteria decision-making (MCDM) problem that provides a framework for comparing and selecting suppliers (Kuo et al., 2015). The aim of supplier selection is to identify and evaluate suppliers and select the suppliers that meet the requirements of the company. Both

quantitative and qualitative criteria are used in these processes. The criteria are determined according to the requirements of the company (Punniyamoorthy et al., 2011). Most common criteria in supplier selection are, quality, cost and delivery performance (Rezaei et al., 2016).

Supplier evaluation and selection is a cross-functional group decision-making problem and the decision making team contains experts/decision makers from different departments such as procurement, R&D, quality assurance and finance (Chou and Chang, 2008). The priorities of decision makers should be identified and considered in the supplier selection process. A wrong supplier selection may cause the following effects (Chen and Wu, 2013; Paul, 2015):

- Increase the number of defective products,
- Cause delays in production and delivery of products,
- Lead to loss of profit within the entire SC,
- Disrupt customer satisfaction and the reputation of the company,
- Cause risk events.

The supplier evaluation and selection literature is very extensive. Various individual and integrated approaches have been proposed for supplier evaluation and selection in the literature (Yurtsever and Oktay Fırat, 2013; Govindan et al., 2015). Some of the methods are listed in the following;

- AHP (Kull and Talluri, 2008; Lee, 2009)
- Analytic Network Process (ANP) (Görener, 2009; Nekooie et al., 2015; Kuo et al., 2015)
- Data Envelopment Analysis (DEA) (Wu, 2009; Chen, 2011)
- Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) (Chen, 2011)
- Mathematical Programming Models such as linear programming, integer programming, multi-objective programming and goal programming (Kull and Talluri, 2008)
- Simple Multi Attribute Rating Technique (SMART) (Chou and Chang, 2008)
- Neural Network (Ha and Krishnan, 2008)
- Fuzzy Logic (Paul, 2015; Chou and Chang, 2008; Lee, 2009)

- Decision-Making Trial and Evaluation Laboratory (DEMATEL) (Kuo et al., 2015)
- VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) method (Kuo et al., 2015)

These methods are applied in an individual or integrated way to deal with supplier selection problem. According to Hamdi et al. (2015), mathematical models are the most common quantitative research techniques in supplier evaluation and selection literature. Ho et al. (2010) examined the articles on the multi-criteria decision making approaches for supplier evaluation and selection from 2000 to 2008 in terms of the applied approaches, criteria and inadequacy of the approaches. Out of 78 journal articles reviewed, 14 articles proposed DEA, 9 articles applied various types of mathematical programming models, 7 articles applied AHP, 7 articles used Case-based reasoning, 3 articles proposed ANP, 3 articles used fuzzy set theory, 2 articles used SMART and one article proposed Genetic Algorithm to evaluate and select suppliers. 32 out of 78 reviewed articles include integrated approaches.

Govindan et al. (2015) reviewed 36 articles on green supplier evaluation and selection from 1997 to 2011. According to their review, 6 out of 36 articles proposed AHP, 4 papers proposed ANP, and 1 proposed mathematical programming for the green supplier selection process. 14 papers proposed other approaches and 8 papers used integrated approaches.

AHP is one of the most used methods for supplier selection (Chan and Wang, 2013b; Govindan et al., 2015; Oktay Firat et al., 2017). It is a simple, easy and understandable method to deal with subjectivity in problems. In AHP, several alternatives are assessed relative to each other according to multiple criteria (Kull and Talluri, 2008). Similarly, the multiple criteria are assessed relative to each other due to a determined goal. Integrated AHP approaches are very common in the supplier selection literature (Kull and Talluri, 2008; Ha and Krishnan, 2008; Lee, 2009; Hamdi et al., 2015). Punniyamoorthy et al. (2011) developed an integrated model of structural equation modeling and fuzzy AHP for supplier selection.

DEA is another popular method in supplier selection. Wu (2009) presented a hybrid model using DEA, decision trees (DT) and NN for the evaluation of supplier

performance. Suppliers are clustered as efficient and inefficient by using DEA and a trained decision tree model is applied to new suppliers. Görener (2009) used the ANP for supplier selection. The advantage of ANP is the ability to capture the interdependencies between the evaluation criteria.

Various authors used fuzzy logic to take into account the uncertainty in preferences of decision makers. Chan and Kumar used fuzzy extended analytic hierarchy process (FEAHP) to cope with different criteria. Nekooie et al. (2015) applied fuzzy goal programming approach for supplier selection problem considering qualitative and quantitative risk factors. Lima Junior et al. (2014) performed a comparative analysis of Fuzzy TOPSIS and Fuzzy AHP methods for supplier selection.

Kuo et al. (2015) proposed a hybrid MCDM model combining the DEMATEL method with ANP (DANP) and VIKOR for green supplier selection. The proposed method is used to determine the weights and causal relationships among supplier selection criteria and VIKOR method is used to select green suppliers. Rezaei et al. (2016) proposed the Best-Worst Method (BWM) for supplier segmentation that is a novel comparison-based MCDM method. BWM is first proposed by Rezaei in 2015. In this MCDM model, first the best (most important) and the worst (least important) criteria are identified (Rezaei, 2015). Then, the decision maker makes pairwise comparisons between these two criteria and the others. The weights of the criteria are determined by solving a maximin problem. According to the results of Rezaei (2015), BWM gives better results than AHP in terms of various evaluation criteria such as consistency ratio, total deviation, etc.

4.4.2. Supplier Evaluation and Selection Criteria

The quality of the supplier evaluation and selection process highly depends on the effective selection of the criteria (Rezaei et al., 2016). Supplier selection problem includes a myriad of quantitative and qualitative criteria (Arioğlu Akan et al., 2014; Paul, 2015; Nekooie et al., 2015). Multiple criteria are used in order to incorporate different aspects in evaluating suppliers such as quality and recycling issues. Supplier criteria should be appropriate with the requirements of the company and applicable to all suppliers that will be evaluated (Şahin and Supçiller, 2015). In addition, these criteria should be relevant to the sector and activity. The importance of supplier selection criteria depends on business priorities and strategies of the focal company (Govindan et

al., 2015). Most of the studies in the supplier selection literature ignore the compliance between supplier evaluation criteria and the corporate strategy (Chou and Chang, 2008).

Hundreds of criteria have been proposed for supplier evaluation and selection in the literature. The most common criteria are cost, quality, deliverability and service (Che and Wang, 2010; Chen and Wu, 2013). According to the literature review of Ho et al. (2010) on 78 articles between 2000 and 2008, the most popular criteria are determined as follows respectively: quality, delivery, price/cost, manufacturing capability, service, management, technology, research and development, finance, flexibility, reputation, relationship, risk, and safety and environment.

Khaleie et al. (2012) used four main criteria for supplier selection: quality, price/cost, delivery and, company and technology ability. Lima Junior et al. (2014) used five decision criteria; i) quality, ii) price, iii) delivery, iv) supplier profile related to supplier reputation and financial health, and v) supplier relationship related with the degree of cooperation and trust.

Some of the main supplier evaluation and selection criteria and related indicators are given in the following (Chou and Chang, 2008; Ha and Krishnan, 2008; Thanaraksakul and Phruksaphanrat, 2009; Chen, 2011; Khaleie et al., 2012; Heidarzade et al., 2016):

- **Financial criteria:** Cost/price, financial performance, financial status of the supplier (financial stability, market share, annual revenue, etc.), cost reduction capability
- **Quality:** Number of rejected items, six sigma programs, Total Quality Management (TQM), quality management practices and systems, quality award, quality certification, quality staff capability, etc.
- **Delivery performance:** On time delivery rate, delivery speed, lead time, delivery flexibility, delivery reliability, consistent delivery, packing ability
- **Service:** Service standard, after sale service quality, service attitude, responsiveness, improvement capability, guarantee and compensation
- **Production capability and performance:** Process capability, historical performance, production control ability, R&D rate, design and development capabilities, capacity utilization

- **Flexibility:** Flexibility of suppliers in the changes of their environment such as political and financial issues
- **Technology:** Technological capabilities, usage of technology, IT level, communication system, e-commerce capability
- **Geographical location:** Distance
- **Management and Organization:** Organizational control, employment relations, organizational culture and strategy, internal audit, data administration
- **Reliability**
- **Business Relations:** Mutual negotiation, trust
- **Reputation:** Industrial reputation, previous image, previous sales

Thanaraksakul and Phruksaphanrat (2009) reviewed 76 papers and determined the frequency of selected supplier selection criteria. Some of these criteria are represented in Table 4.2 with their frequency and percentage within reviewed articles. In addition to quality, delivery and cost criteria, most of the reviewed articles consider production facility, flexibility and technical capacity related criteria too.

Table 4.2. Supplier selection criteria in the reviewed articles (Thanaraksakul and Phruksaphanrat, 2009)

Criteria	Number of papers	Percentage (%)
Quality	74	97.37
Delivery	72	94.74
Cost	72	94.74
Production facility and capacity	52	68.42
Flexibility and reciprocal arrangement	52	68.42
Technical capacity and support	49	64.47
Financial status	40	52.63
Performance history	23	30.26
Warranties and claim policies	15	19.74
Environmental and social responsibility	6	7.89

Chen (2011) gave a table of some important criteria including quality, deliver on time, historical performance, guarantee and compensation, technical capability, geographic location, packing ability, communication system, etc. Punniyamoorthy et al. (2011)

used 46 sub-criteria that represents 10 main criteria for supplier selection: management and organization, quality, technical capability, production facilities and capacities, financial position, delivery, service, relationship, safety and environment concern, and cost. They made a survey of 151 respondents to determine the relative weights of these criteria.

In recent years, supplier selection problem incorporates approaches from different disciplines and goes beyond traditional cost minimization and profit maximization objectives. Especially the use of intangible and qualitative factors has increased (Rezaei et al., 2016; Govindan et al., 2013; Punniyamoorthy et al., 2011). Some examples to these factors are supplier relationships, reputation of the company, SC risk, corporate social responsibility, business continuity, etc. (Govindan et al., 2015; Rezaei et al., 2016). Most of these studies have been done in recent years. The integration of new dimensions to supplier selection increased the complexity of the problem. Some of the developments that lead to the changes in supplier evaluation and selection criteria can be listed as follows (Rezaei et al., 2016; Govindan et al., 2015):

- i) Increased dependency on suppliers,
- ii) Increased globalization and offshoring,
- iii) Increased awareness of customers on sustainability related issues,
- iv) Changes in customer requirements and preferences,
- v) Rise in regulations, etc.

Although extensive studies have used traditional supplier evaluation and selection criteria such as price, quality, delivery performance and flexibility, a limited number of researchers addressed sustainability issues in their study (Wan Mahmood et al., 2014; Kuo et al., 2015). Economic, environmental and social dimensions must be included in supplier selection (Govindan et al., 2015). Rapid depletion of natural resources, government regulations, environmental legislations, and increasing awareness on sustainability drive companies to consider sustainability issues more in their processes. Er Kara et al. (2016) made a literature review on the indicators that are used to measure the sustainability of suppliers. They classified sustainable supplier evaluation and selection criteria under the three dimensions of sustainability.

Rezaei et al. (2016) incorporated environmental and business criteria to supplier selection problem. They used eight criteria in their study: cost of delivery, lead time, non-competitor on specialties, price, production facilities and capacity, quality, compliance on certification, and sustainability performance. Wan Mahmood et al. (2014) focused on the sustainable supplier selection process and determined the most common criteria for the evaluation and selection of suppliers. They listed the sustainable supplier selection criteria based on a literature review: i) Economic criteria: service, quality, cost, technology capability, and delivery, ii) Environment criteria: green image, pollution control, green competencies, and green product, iii) Social criteria: safety and health, and employment practice. They also examined the interdependency between these criteria. Govindan et al. (2013) used fuzzy TOPSIS to rank suppliers according to their sustainability performance. They used the following criteria; i) Economic criteria: cost, delivery reliability, quality, technology capability, ii) Environmental criteria: pollution production, resource consumption, eco-design, environmental management system, iii) Social measures: employment practices, health and safety, local communities influence, contractual stakeholders influence.

Kuo et al. (2015) used seventeen criteria concerning environmental and management system dimensions to evaluate green suppliers in an electronics company. Some of these criteria are environmental permits and reporting, pollution prevention and resource reduction, hazardous substances, air emissions, company commitment, management responsibility, risk assessment and management, worker feedback and participation, etc. These criteria are identified by using the Code of Conduct of the Electronic Industry Citizenship Coalition (EICC) that is a set of standards on social, environmental and ethical issues in the electronics industry SC (EICC, 2016). Govindan et al. (2015) reviewed the articles that consider environmental factors in green supplier evaluation and selection from 1997 to 2011. According to their review, the most common criterion considered in evaluating the environmental performance of suppliers is environmental management system followed by green image, environmental performance, design for environment, corporate and social responsibilities, environmental authentication, environmental improvement cost, green logistic, environmental certification, use of environmentally friendly material and technology, waste management, reuse, recycling, and green design.

Lima-Junior and Carpinetti (2016) proposed a MCDM model to assist in selecting and weighting the supplier selection criteria. They combined fuzzy Quality Function Deployment (QFD) to determine the weights of criteria with the assessment of the difficulty of data collection for each criterion. The proposed model also classified the criteria into four groups based on the weights of the criteria and difficulty of data collection for this criteria: priority, critical, complementary and costly.

4.4.3. Supply Risk Issue in Supplier Evaluation and Selection

Companies are affected by the risks in other members of the SC. Some past disruptive events have shown the importance of the analysis and management of risks in suppliers and sub-suppliers (Norrman and Jonsson, 2004; Er Kara and Oktay Firat, 2015). In today's competitive and risky business environment, it is very important to work with reliable suppliers. Supplier related risks are one of the most frequently discussed risks in the literature (Section 3.3). The number of studies on supply and procurement risk management is growing (Entchelmeier et al., 2006; Hong and Lee, 2013). Supplier evaluation and selection is one of the most important processes for the mitigation of supply and procurement risks. Risk criteria started to gain increasing attention in recent years and a growing number of researchers have been incorporating supplier risk criteria in the evaluation and selection of suppliers (Fang et al., 2016). Supplier evaluation and selection process have gone beyond traditional criteria and the uncertainty in this process have increased. Hence, supplier risk measures have to be defined and incorporated in these processes (Kull and Talluri, 2008). Supply risk is a multidimensional concept and includes various different factors. Ruhrmann et al. (2014) analyzed and modeled the risks and dynamics in the acquisition of new suppliers in low-wage countries. They listed the risks related with procurement as follows: i) exogenous risks: market risks and macroeconomic risks ii) endogenous risks: specific supplier risks including capability, quality, confidence, communication, etc.

There are a lot of studies that incorporate risk issue into their mathematical programming model for supplier selection. However, most of the studies incorporate risk by adding a risk-based goal and one or a few variables that represent suppliers' risks. Hamdi et al. (2016) developed two mixed integer programs for supplier selection and order allocation problem under local supplier disruption risk. The first one

considers a risk-neutral decision maker who wants to maximize the expected profit. The second program considers a risk-averse decision maker who aims to minimize operational loss. Patra and Mondal (2015) developed three supplier selection models in crisp and fuzzy environments by considering two objective functions; profit maximization and risk minimization. They also applied a sensitivity analysis for different risk values. PrasannaVenkatesan and Goh (2016) developed a multi-objective mixed integer linear programming model for supplier selection and order quantity allocation under disruption risk. Suppliers are ranked using fuzzy AHP and fuzzy PROMETHEE, and then a set of Pareto-optimal solutions are obtained by multi-objective particle swarm optimization (MOPSO) algorithm. They used cost, customer service and risk criteria for supplier evaluation and selection. The sub criteria under risk category are output flexibility, contractual commitments, labor issues, visibility, geographical location and political/economic stability.

Although there is a vast amount of studies on supplier evaluation and selection, limited number of researchers explored this problem under a risk management perspective (Chen and Wu, 2013; Paul, 2015). In addition to critical success factors, negative aspects of suppliers should be incorporated in evaluating and selecting suppliers (Lee, 2009). Chen and Wu (2013) considered supplier evaluation and selection as a SCRM problem. They proposed a modified failure mode and effects analysis method with AHP for supplier selection from the SC risk perspective. The weights of supplier selection criteria and sub-criteria are determined with AHP. They used six main criteria in their study: quality, cost, deliverability, service, technology and productivity criteria. Mavi et al. (2016) studied on supplier selection problem in the context of SCRM. They used Shannon entropy for weighing criteria and fuzzy TOPSIS for ranking suppliers. Nine criteria are used to evaluate suppliers; quality, on time delivery, performance history and six risks including supply, demand, manufacturing, logistics, information and environmental risks.

Hamdi et al. (2015) reviewed and classified 124 papers from 2003 to 2014 related with supplier selection based on SCRM. According to their review, the most frequent risks are reliability risk, variability of customers' requests, risk of sharing information, and quantity discounts, respectively. They gave a comprehensive list of the treated risks in the reviewed articles. They also classified the supplier selection approaches in the

reviewed papers under four categories: i) Mathematic: linear programming, goal programming, heuristic, etc. ii) Simulation: discrete event, Monte Carlo, Petri net, etc. iii) Qualitative approaches: AHP, ANP, Game Theory, TOPSIS and FVICOR, iv) Combined approaches: Fuzzy Analytic Hierarchy Process (FAHP) and TOPSIS, AHP and goal programming, etc.

There are very few articles that consider risk based on various perspectives. Knemeyer et al. (2009) proposed adding “catastrophic risk exposure” criteria in supplier selection as an alternative countermeasure to cope with catastrophic risks. Kull and Talluri (2008) proposed a model that integrates AHP and goal programming for supplier selection in the presence of supply risk and product life cycle considerations. They considered the following failure events: delivery, cost, quality, flexibility and general confidence failures. Pairwise comparisons of risk dimensions are performed with respect to both their relative likelihood and impact on business performance. Lee (2009) proposed a FAHP model that incorporates benefits, opportunities, costs and risks to evaluate suppliers based on different aspects. Multiple factors that positively or negatively affect the success of the relationship were considered. The sub-criteria in risk category are supply constraint, buyer-supplier constraint and supplier’s profile. Yücenur et al. (2011) used FAHP and fuzzy ANP to evaluate different criteria such as service quality, cost, risk factors, and supplier’s characteristics in global supplier selection. The risk factors criteria include the following attributes: order delays, political stability, economy, customer complaints, geographical structure, terrorism, climate conditions and cultural differences.

Xiao et al. (2012) used an integrated approach of fuzzy cognitive map and fuzzy soft set model for supplier selection considering four risk criteria including quality risk of the product, service risk, supplier’s profile risk, and long-term cooperation risk. Chan and Wang (2013a) proposed an integrated approach based on AHP and fuzzy set theory for supplier risk assessment to solve supplier selection problem. They used five main risk categories: quality, delivery, cost, manufacturing capacity and service. Paul (2015) used a rule-based fuzzy inference system (FIS) for supplier selection considering relevant criteria for managing supply risks. They identified 4 quantitative and 14 qualitative selection criteria. Fuzzy input and output variables are used to incorporate risks due to uncertainty to the model.

Meena and Sarmah (2016) studied on supplier selection and demand allocation problem under supplier failure risk due to disruptive events. They proposed an analytical model and performed a numerical study. Lee (2014) studied on determining the optimal number of suppliers and considered semi-supplier events that can disrupt all suppliers in a specific geographical location. Hong and Lee (2013) proposed a DSS to model risks for the procurement processes in the presence of spot market. A Monte Carlo simulation algorithm called the Expected Profit–Supply at Risk (A-EPSaR) was used to evaluate the performance of each supplier and quantify their risks for supplier selection and order allocation. They classified suppliers into three groups by using expected profit and Supply at Risk (SaR): preferred suppliers, approved suppliers and avoided suppliers.

Li and Zeng (2016) proposed FMEA to assess the risks in the supplier selection process. Evaluation schemes were constructed for cost, delivery, quality and service criteria. Failure modes are identified for each criterion and ranked in terms of likelihood, impact and detection/control by using a 10-point scale. Finally, suppliers were ranked according to both original and risk-discounted scores for comparison.

Some researchers studied on supplier selection in an uncertain and risky SC environment. Wu and Olson (2008) used chance-constrained programming, DEA and multi-objective programming models for vendor selection in an uncertain environment. Different risk embedded attributes are modeled with probability distributions (distributions of costs, acceptance failure and late delivery) and simulated data is used. Amorim et al. (2016) proposed a stochastic mixed-integer programming model for supplier selection in the processed food industry. They considered the uncertainties in supply; uncertainty in available quantity and lead-time. Their model focuses on sourcing of perishable raw materials and aims to maximize profit and minimize risk of low customer service level. Sawik (2011) formulated a single-period supplier selection and order allocation problem in make-to-order environment with risk as a stochastic single or bi-objective mixed integer problem. The model aims to minimize total cost and reduce the impact of the delay risk. Value-at-risk and conditional value-at-risk measures are used to control delayed supply risk. In a later study, Sawik (2014) proposed a stochastic mixed integer programming approach for the joint supplier selection and scheduling of customer orders in the presence of SC disruption risks. He used conditional value-at-risk as a risk measure. The results showed that supplier reliability is

a key parameter for supplier selection. Fang et al. (2016) proposed a probability based multi criteria optimization model including both risk criteria and supplier performance in order to examine the tradeoff between cost and risk factors. They used value-at-risk (VaR) for the evaluation of operational risks such as defects, late delivery and uncertain demand. They also used conditional value-at-risk (CVaR) for the assessment of disruption risks including natural and man-made disasters.

Global supplier selection problem is more complex and risky than domestic sourcing. For global supplier selection, Chan and Kumar (2007) used fuzzy extended analytic hierarchy process (FEAHP) to cope with different criteria such as cost, quality, service performance and supplier's profile including risk factors. The discussed risk factors are related with political stability, geographical location, economic status, and terrorism. According to their empirical study, political stability risk criterion has a high weight and the assessment of terrorism risk may be biased and should be evaluated carefully. Schoenherr et al. (2008) used action research and AHP for an offshore sourcing decision. 17 risk factors were identified through iterative and structured discussions. Some of these risk factors/ performance measures are listed as follows: comply with ANSI (American National Standards Institute) standards, product quality, competitor cost, demand risk, logistics risk, wrong partner risk, overseas risk, supplier risk, supplier's supplier management risk and natural disasters/ terrorists.

A limited number of researchers include both qualitative and quantitative criteria. Wu et al. (2010) proposed a fuzzy multi-objective programming model for supplier selection considering risk factors. They used simulated historical data for both quantitative and qualitative supplier selection risk factors. Quantitative risk factors are cost, quality and logistics; qualitative risk factors are economic environmental factors and vendor ratings. Nekooie et al. (2015) took into account both high probability - low impact and low probability – high impact supply disruptions in supplier selection problem. They used ANP to obtain priorities of the determined qualitative risk factors to consider the interdependence between them. The most important risk factors are determined as excessive handling due to border crossing or to change in transportation modes, data information security and cost uncertainty according to their three suppliers, respectively. They also incorporated two quantitative criteria; delay and defect rate in the mathematical model. Chou and Chang (2008) presented a strategy-aligned fuzzy

SMART approach by using both qualitative and quantitative criteria for supplier selection. A final decision maker incorporates the supply risks of suppliers in his/her assessments by using a risk coefficient.

4.4.4. Clustering Approaches in Supplier Evaluation and Selection

Companies may prefer to identify more than one supplier or there may be capacity constraints for suppliers. Instead of selecting one supplier, generating supplier groups based on predetermined features is more advantageous. Many large companies work with hundreds of suppliers to provide raw materials, parts, components, sub-assemblies and other components. Even some large-scale enterprises have thousands of suppliers (Zhang et al., 2006). Categorization of these suppliers based on different attributes is very advantageous to develop different supplier management plans and strategies for each group of suppliers. Hallikas and Lintukangas (2016) determined the importance of some activities to mitigate supply risk according to the results of a survey in Finnish companies. According to the respondent companies, the fourth most important mitigation activity is avoidance of certain suppliers. Clustering may help to identify and eliminate risky suppliers.

In real business life, companies generally categorize suppliers according to some basic properties such as product categories they provided, company size, geographical location, etc. (Zhang et al., 2006). There is a need to use more carefully identified and more specific characteristics to categorize suppliers. Clustering suppliers aims to identify a group of alternative suppliers or group and eliminate suppliers according to selected criteria (i.e.; clustering suppliers according to their operational performance). Clustering techniques are useful in detecting similarities and dissimilarities between different data sets (Khaleie et al., 2012).

Clustering suppliers provides the following advantages for companies:

- i) It helps to obtain manage-able smaller supplier groups, reduce the number of alternatives and increase the simplicity and flexibility of the supplier selection process (Şahin and Supçiller, 2015; Bottani and Rizzi, 2008).

- ii) It provides the opportunity to develop different plans and strategies for each supplier group to manage suppliers, enhance supplier relationship management and improve supplier performance management systems.
- iii) It is helpful when there are very large number of supplier combinations for different parts of a product (Che and Wang, 2010). It provides the chance to eliminate different groups of suppliers according to predetermined criteria.
- iv) Providing alternative suppliers helps to act quickly in the case of unforeseen interruptions in the supply of raw materials. Existence of a qualified vendor pool allows companies to substitute a disrupted supplier easily and quickly with a new supplier and increase the efficiency of the supplier risk management.
- v) It provides the opportunity of selecting a group of suppliers when the company prefers to select more than one supplier for various reasons such as capacity constraints of suppliers (Heidarzade et al., 2016).
- vi) Today the scope and the number of supplier evaluation and selection criteria have increased. Clustering is very advantageous in dealing with large volumes of data.

The supplier clustering literature is not rich. Table 4.3 gives some articles that performed supplier-clustering analysis. The table includes the reference, methodology, supplier evaluation / selection criteria, number of suppliers and the number of extracted clusters.

Zhang et al. (2006) categorized suppliers based on the suppliers' business behaviors by using k-means type subspace clustering algorithm, Feature Weighting K-means (FW-KMeans). They used a data-driven method and used a large volume of business transactions data to derive the suppliers' business behaviors. Ha and Krishnan (2008) proposed a hybrid model incorporating AHP, DEA and NN for supplier evaluation. A combined supplier score is calculated by considering both qualitative and quantitative factors that affect SC performance. Then self-organizing map (SOM) which is a neural clustering method is applied by accounting only quantitative criteria to find homogenous supplier clusters and create a supplier map.

Table 4.3. Literature on supplier clustering

Reference	Methodology	Supplier evaluation / selection criteria	Number of suppliers	Number of clusters
Che and Wang, 2010	A hybrid approach based on K-means, simulated annealing algorithm (SA), convergence factor particle swarm optimization (CPSO) and the Taguchi method abbreviated as KSACPSO	Product cost, product quality, procurement time	70	3
Şahin and Supçiller, 2015	A hybrid model based on AHP, TOPSIS and K-means method	Quality, cost, delivery, service	20	4
Khaleie et al., 2012	A novel intuitionist fuzzy clustering approach	Quality, product price, on-time delivery, logistics cost, IT level, environment adaption degree	7	*
Heidarzade et al., 2016	Hierarchical clustering-based method based on a new distance formula for interval type-2 fuzzy sets	Quality, total cost, technological capabilities, buyer-supplier partnership, geographical location, flexibility, production performance, just in time delivery	8	3
Zhang et al., 2006	K-means type subspace clustering algorithm, FW-Kmeans	Amount of items in each order, order frequency, product quality, product arrival time, etc.	974	60
Haghighi et al., 2014	Fuzzy Linguistic Preference Relations (LinPreRa) based AHP and fuzzy c-means algorithm	Price, delivery, quality, reserve capacity, geographical location, financial position, commitment to quality, communication openness, willingness to share information, supplier's effort in promoting JIT principles, etc.	43	4
Ha and Krishnan, 2008	A hybrid model incorporating AHP, DEA and NN for supplier evaluation and self-organizing map for clustering analysis of suppliers	Quality system outcome, claims, quality improvement, response to claims, on-time delivery, internal audit, data administration	27	6

* An object can belong to more than one cluster in clustering fuzzy datasets

Che and Wang (2010) developed a hybrid approach, KSACPSO, based on K-means, simulated annealing algorithm (SA), convergence factor particle swarm optimization (CPSO) and the Taguchi method to discriminate types of part suppliers. Parts suppliers

are discriminated based on product cost, quality and procurement time. They also used ANOVA and Scheffe's multiple comparison to compare the convergence values of six algorithms and find the optimal supplier clusters.

Che (2012) proposed two optimization models for supplier clustering and selection respectively. Supplier clusters are determined by using the customer demand attributes such as production cost, product quality and production time. The two mathematical models are solved by a two-phase method. Phase 1 integrates k-means and simulated annealing algorithm with the Taguchi method (TKSA) to solve Model 1 and Phase 2 uses AHP to weight each factor and then uses simulated annealing algorithm with the Taguchi method (ATSA) to solve model 2. Şahin and Supçiller (2015) proposed a DSS for supplier selection and evaluation problem. Supplier selection criteria are weighted using AHP and then suppliers are ranked according to the weighted scores using TOPSIS. These suppliers are then clustered using k-means method into four clusters.

Some of the researchers used fuzzy values to show the preferences of decision makers and applied fuzzy clustering. Bottani and Rizzi (2008) integrated AHP, cluster analysis (CA) and fuzzy logic to cluster and rank suppliers and purchased items. They grouped suppliers by performing cluster analysis and then applied AHP. Khaleie et al. (2012) proposed an intuitionist fuzzy clustering-based method for supplier selection based on intuitionistic fuzzy value for decision makers' opinion. They used four main criteria (quality, price/cost, delivery and, company and technology ability) and totally 8 sub-criteria. Haghighi et al. (2014) used Fuzzy Linguistic Preference Relations (LinPreRa) based AHP to weight the supplier selection criteria and then used fuzzy c-means algorithm twice to cluster suppliers based on suppliers' capabilities and willingness criteria. The results of the clustering algorithm is used to segment suppliers. Heidarzade et al. (2016) used interval type-2 fuzzy values to represent decision makers' preferences and proposed a hierarchical clustering-based method with a new distance formula for supplier selection problem.

There are also studies that focus on supplier segmentation by computing the aggregated scores of suppliers in the literature. Supplier segmentation aims to classify suppliers to different groups generally with the aim of building different supplier management and development strategies and programs (Rezaei et al., 2015). Suppliers are commonly

segmented into four segments based on two dimensions (Rezaei and Ortt, 2013). Matook et al. (2009) performed factor analysis on the risk rating data of 17 suppliers. Risk ratings were gathered through questionnaire and expert discussions. Two factors are extracted from 7 different risk types. The factor scores of the suppliers are plotted in two dimensions and six supplier groups are identified by using this factor plot. Rezaei and Ortt (2013) combined different supplier typologies based on the capabilities and willingness of suppliers for cooperation. They proposed fuzzy AHP to segment suppliers. In a later study, Rezaei et al. (2015) used a new MCDM method, BWM, for supplier segmentation based on suppliers' capabilities and willingness for collaboration.



5. A NEW SUPPLY CHAIN RISK MANAGEMENT MODEL BASED ON DATA MINING

This chapter contains the development of a general conceptual model for a SCRM framework supported by DM tools and techniques. Then, the general steps and components of the model are explained in detail. A general guideline is developed in order to explain how to build and implement the DM-based framework for SCRM. The general model and its main steps are explained in detail. The implementation issues, advantages and limitations of the proposed model are discussed.

5.1. A General Framework for the Development of a Data Mining based Supply Chain Risk Management Model

Despite the industrial interest in BI in SCM and SCRM, the academic literature on the use of BI and DM techniques in risk management is rare (Lee and Kulkarni, 2011). This thesis examines the use of BI and DM techniques in SCRM and develop a risk management model utilizing DM tools and techniques. Figure 5.1 represents the general steps of a SCRM system and some of the BI tools and techniques that may be used in these steps.

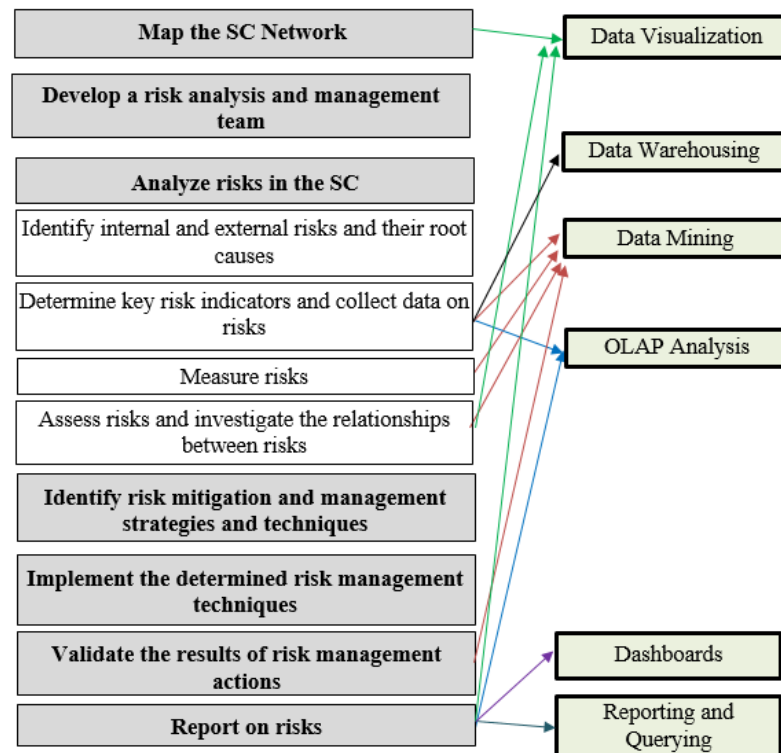


Figure 5.1. BI tools and techniques in SCRM

Today's information technologies provide the opportunity to gather, store and analyze a diverse set of risk-related data from heterogeneous data sources. BI tools and techniques are used to convert the risk data and metrics into information and knowledge that can be used in SCRM. DM is proposed as a tool that can be used to assist and aid decision makers in SCRM. DM algorithms may be used for the identification, evaluation and management of different SC risks. DM is one of the core technologies for today's business life. It helps companies to discover risks and opportunities easily. DM is a tool that supports the decision-making and problem solving processes (Giudici and Figini, 2009). The main motivation of the study is to provide a framework for the implementation of DM algorithms in SCRM. The aim of the proposed DM-based SCRM model is to provide a comprehensive guideline that will assist companies to develop an effective DM-based risk management system and implement DM tools for mitigating their risks. The formulation of the proposed model depends on the literature review on SCRM and BI fields and, interviews and discussions with both SC and IT experts. The proposed approach is holistic and incorporates various risk types in SCs and different DM tools. To the best of our knowledge, a DM-based SCRM model has not already been addressed in the literature. Hence, this model fills a gap in the SCRM literature.

The flowchart for the development and implementation of the DM-based SCRM model is given in Figure 5.2. General steps of a SCRM process are broadened by inserting a DM module. To the best of our knowledge, this is the first model that integrates the main steps of SCRM and DM in a unique risk management structure. Berry and Linoff (2004) proposed to embed DM in a corporate customer relationship strategy in order to take required actions according to the results of DM (what is learned by DM). With a similar approach, we proposed to embed DM in a SCRM strategy. DM module includes the application of DM algorithms in SCRM. Besides developing a SCRM platform for the company, the proposed model provides a framework for the organization to select and apply DM applications for assisting in SCRM. The proposed risk management model makes the company smarter about SC risks.

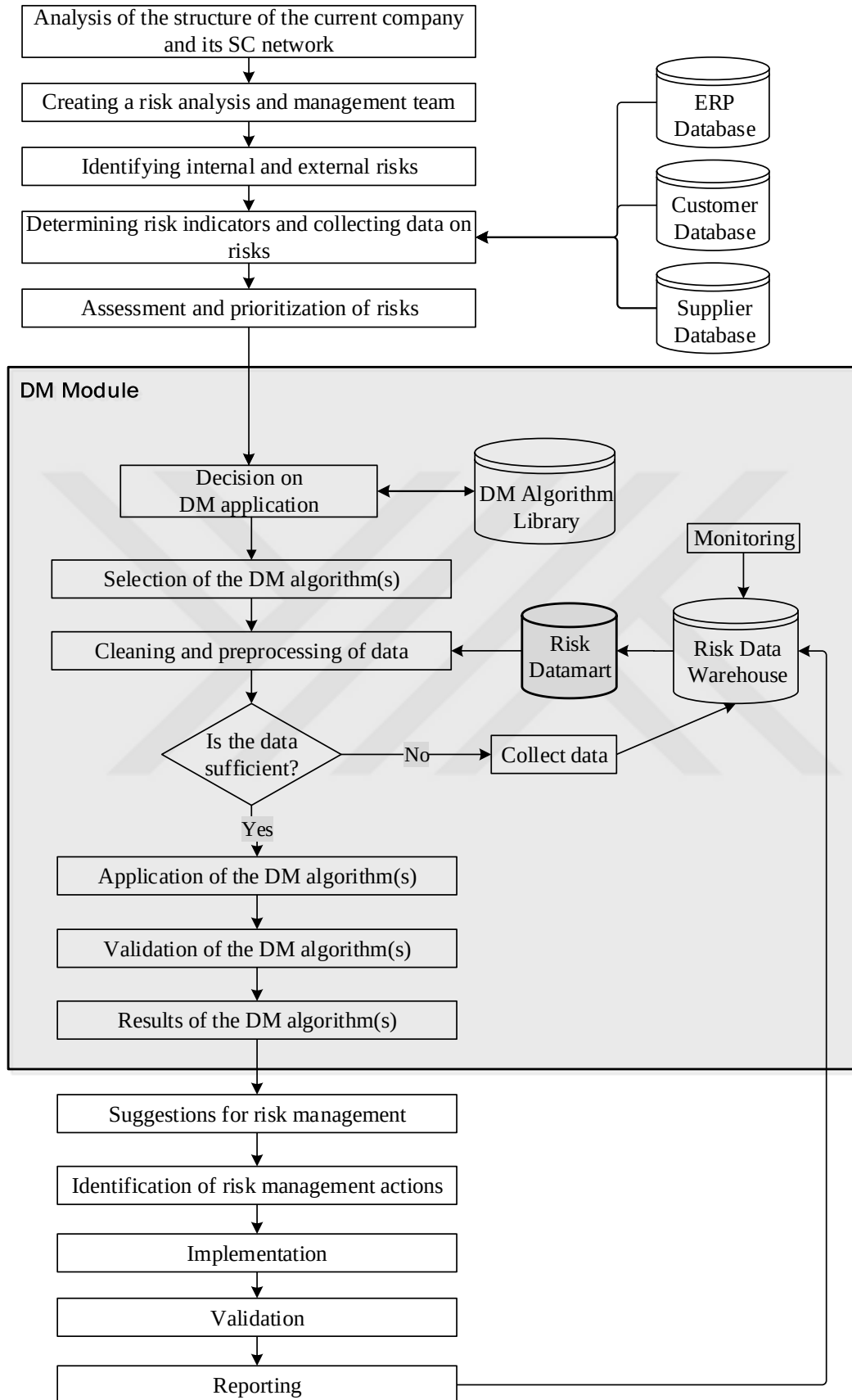


Figure 5.2. Flowchart for the development of the DM-based SCRM model

SCs contain various risk types and risk management decisions. SC risks and their structure differ according to the industry and even to the company. All of the risks should be evaluated by considering the risk types, the risk attitude of the company and the structure of the current sector. Hence, the scope of the research is limited to the design of a general DM-based SCRM framework and its application for a selected risk problem in a specific manufacturer in Turkey.

This framework offers a comprehensive guidance for companies to systematically monitor and manage their risks and apply DM algorithms in their risk management practices. Data warehouse collects and stores risk related data and indicators. DM module helps to find hidden, previously unknown and helpful information from the company's datawarehouse. This thesis focus on building a general model rather than specifying each technique of DM. Amundson (1998) used metaphor of a "lens" in order to explain the importance of theories in research and knowledge base. Done (2011) adapted this approach of Amundson to illustrate the relationship between knowledge management and SC performance. We adapted the lens approach used in Amundson (1998) and Done (2011) to represent the role of SCRM and DM fields in the development of the DM-based SCRM model. As it is seen from Figure 5.3, a lens is directed towards the objective of the development of an effective DM-based SCRM model. The studied model changes with the developments in the SCRM and DM areas and, the technological innovations. The lens can only capture the environment that is within the sight of the observer (Amundson, 1998). The objective also varies based on the characteristics of the observer and the lens. Therefore, the development of a DM-based SCRM is dependent on the structure of the sector, SC network and risk attitude of SC executives.

Identifying and managing the SC risks is a hard and costly process. Risk is due to lack of information about the future. Therefore, DM algorithms are expected to be efficient in SCRM. DM algorithms can be used in different stages of SCRM such as risk identification, risk categorization, early warning for risk, etc. DM has the ability to discover the sources of risk, noticing patterns and relationships, and improve prediction capability by analyzing the past data. Prediction of SC risks is important for applying proactive methods to reduce the effects of the risks. DM is also a powerful tool for risk prediction (Dani, 2009).

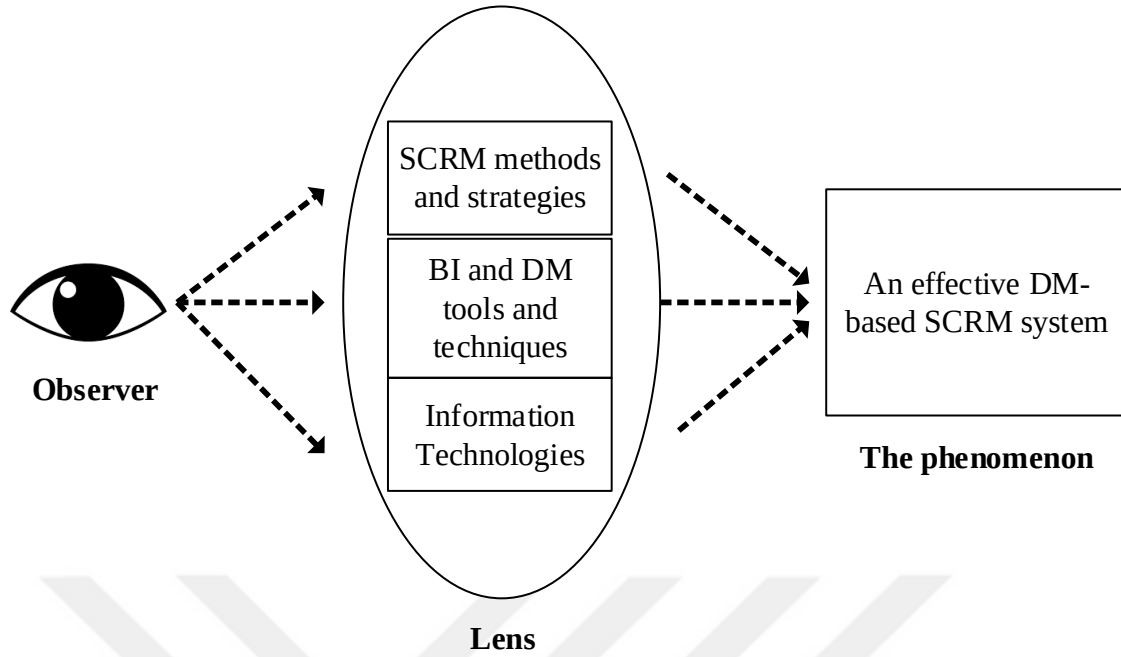


Figure 5.3. Application of the lens metaphor for the DM-based SCRM model (adapted from Amundson (1998) and Done (2011))

DM is appropriate for real time processing. Thus, it can be used in risk monitoring step in order to identify and detect new risks and the changes in the current risks immediately. DM is also suitable for interactive and distributed knowledge discovery applications. Various softwares supply interactive environment for DM tasks. All of these properties point out the potential power of DM techniques for SCRM.

DM can help companies to gain a better understanding of the SC risks, their critical effects and interdependencies between them. Thus, proactive and preventive actions can be developed according to the results of DM. DM tools and techniques may help to increase the visibility and responsiveness of SCs. DM techniques have the capability to reduce risks and improve decision making processes. Besides negative risks, DM can provide the discovery of possible opportunities for the companies too.

5.2. Analysis of the structure of the company and its SC network

The first step in the DM-based SCRM model is the analysis of the structure of the current company and its SC network. The SC network including the focal company, its suppliers, service providers, customers and other stakeholders should be analyzed and the overall structure and characteristics of the network should be examined.

Visualization techniques may be used for a better SC network representation (Basole and Bellamy, 2014). This step is required in order to gain information about the risk exposure and resiliency levels of the company by examining its business, sector, SC network, risk attitude and current risk management practices. This step contains the following five tasks:

i) Collect information about the company: The proposed SCRM model starts with gathering data about the company. Although SCRM models provide general steps that guide companies, each risk management model is particular for a specific company. A successful SCRM model should be compatible with the mission, business objectives and strategy of the company. Firm's size, experience, business environment, sector and the structure of the SC network are other factors that have a high impact on the type and distribution of risks, and identification of risk mitigation strategies. Besides, the properties of the sector and the current position of the company should be investigated in this step. All of these information are required to develop a risk management model that meets the requirements and needs of the company.

ii) Map the SC network: Identifying the structure of the SC network will help to discover the internal and external actors, the relationships and possible risk factors in the SC network and the position of the company in the SC. SC maps provide a big picture of the network and increase the visibility of the SC. Visual analysis of the SC network and processes help to discover and address potential risk areas (SCRLC, 2011). Documentation of material, information and cash flows within the SC is also important to understand the risks associated with different processes.

iii) Determine the risk attitude/tolerance level of the firm: Risk attitude describes the risk taking properties and behaviors of companies (March and Shapira, 1987). Risk attitude of companies affects risk determination, assessment and perception, and choice of risk mitigation activities (Liu and Nagurney, 2011). Therefore, risk attitudes and tolerance levels of companies should be evaluated and determined at the beginning of the risk management procedure. Basically there are three different risk attitudes: risk-averse, risk-seeking and risk-neutral (Heckmann et al., 2015). There may be no tolerance of risk for complying with laws and regulations in some sectors such as

healthcare industry (Deloitte, 2010). Business objectives and culture of the company also effects the risk attitude of the company.

iv) Examine the risk management framework of the company and previous SCRM practices: Before development of a SCRM model, the current risk management process and previous SCRM practices of the company should be evaluated. The company may prefer to develop a new SCRM model or improve its current risk management framework by adapting the steps of the proposed model.

v) Evaluate the company's resilience level to risks: Previous steps help to gain information about the resilience level of the company in the context of SC risks. Companies can prioritize their critical risk areas and focus their risk management practices into these areas by examining their resilience to different risk factors.

Companies gain information about their risk exposure and resilience levels and, distribution of risks within the SC network by performing these five steps. Each step has an effect on the prioritization of risks, identification of risk management problem (hence the DM problem formulated from it) and the risk response strategy of the company.

5.3. Development of a Risk Management Team and Identification of Risks

After the analysis of the structure of the company and its external environment, the second step is the development of a risk analysis and management team. The sub-steps that are explained in Section 5.2 should be considered when selecting the team members and identifying the number of required people. DM-based SCRM model requires a collaborative approach of a group of employee from various departments with different backgrounds and expertise. A data analyst or DM expert should join to the team for the analysis of risk data and application of the DM tools. The roles and responsibilities of the team members should be identified in detail in order to prevent possible confusions and improve the efficiency of the work force. The risk analysis and management committee may consist of four main types of experts:

- i) Risk management expert
- ii) Domain expert(s)

iii) DM expert

iv) IT experts

A risk management expert or executive is needed to guide other members in the identification and measurement of risks, and determination of risk management actions. Domain experts are people that have expertise in the application domain. Domain experts may be from various functional departments within or outside the company. Domain experts should also be responsible and accountable for the associated risks (risk owners).

The people who have knowledge and expertise for the business areas and processes should be identified in order to identify the risk management team members (Deloitte, 2010). Kinman (2012) suggest to identify the levels of the risk owners depending on the strategical importance of the risk. As an example; macro risks such as political uncertainty should be assigned to senior management. Knowledge mapping concept may be used for the organization and visualization of knowledge. It is a process that aims to identify sources of knowledge (who knows what) and represent the flow of knowledge (Neef, 2005). Knowledge mapping can be used in the identification of the responsible people for different risk types and data.

DM-based SCRM model is based on the analysis of risk data by using DM tools and techniques. Therefore, DM expert has an important and active role for the proposed model. Various names may be used instead of DM expert such as data analyst, data miner, etc. DM expert is responsible for the following tasks: i) identification of the risk data and indicators with other member of the team, ii) determination of data collection methods, iii) development of a data warehouse focusing on risk data with IT experts, iv) transformation of the risk problem to a DM problem, v) selection, specification and application of DM tools and techniques (answers to “Which DM tools and techniques are more suitable for the application?”), vi) interpretation of the results of the DM algorithms and, discussions on the results with domain experts and risk management executives. In addition to the technical knowledge on data analysis and management, DM expert should have a certain level of knowledge about the application domain and SC risks.

Data warehousing and DM requires both technical skills and data management knowledge, hence risk management team should contain people both from technical and business side and, they should have a degree of knowledge in the other areas too (Anderson-Lehman et al., 2004). DM module should be performed by a team consisting of domain experts, data analysts and IT experts (Refaat, 2007). According to Feelders et al. (2000), three types of expertise are needed for the analysis phase of DM. These are knowledge of the application domain, data expertise and DM expertise.

The development of the DM-based SCRM model requires an IT infrastructure; hence, there should be an IT expert in the risk analysis and management team. IT expert(s) is responsible for the development of the required data warehouse and IT infrastructures.

Each DM application may be treated as a new project. Process owner associated with the selected risk problem may be incorporated to the risk analysis and management team. Therefore, the team has a dynamic structure and domain experts vary depending on the application domain of the selected risk problem.

A clear statement of business objectives and requirements is very important for every business model (Stefanovic et al., 2006). Therefore, the risk analysis and management team first identifies and defines the overall objectives and requirements for the SCRM system of the organization. SCRM objectives should be compatible with the business objectives and strategies of the organization (Scheierman, 2017). These objectives are considered in the risk identification and assessment (or prioritization) steps, and the identification of a risk management problem that will be converted to a DM problem (identification of the DM application). Scheierman (2017) listed some questions that will help companies to define their risk management goals and objectives.

The third main step of the DM-based SCRM model is the identification of uncertainties and risks within the current SC. Past risk events, potential risk areas, and root causes of these risks are listed in this step. Companies should consider both internal and external risk factors in their risk management model. There are various methods that can be used in the identification of possible risk events and their risk sources. The most common techniques are; analysis of past data, survey, interview, focus group technique, discussion and field observations (Gill et al., 2008; Thun and Hoenig, 2011; Chen and Wu, 2013; Fowler, 2014). For more information, we refer to Chapter 3.

Risk analysis and management team can also use a combination of these techniques. After the identification of the SC risks, the next step is the identification of risk indicators that can be used to measure and monitor these risks. Identification of risk indicators and collection of risk data are explained in detail in Section 5.4. Different risk factors and their relationship are evaluated after the collection of risk data and an overall risk profile of the company is extracted as a result of these processes. The impacts of risks are also assessed. The loss associated with a risk is measured both in terms of tangible (e.g. effect on revenue and cost) and intangible (e.g. reputation of the company, relationships with other stakeholders, customer trust) factors (Knemeyer et al., 2009; Govindan et al., 2013).

A general assessment of risks help to identify the critical parts of the SC that are more prone to disruptions and prioritize risk areas. This information is used in the identification of the risk problem that will be the main topic of the DM module.

The output of the risk identification and assessment steps may be presented as a risk report that describes the risks the organization is exposed to and the most risky areas (Deloitte, 2010). This report may be used as a guide in the latter steps of the DM-based SCRM model or in further studies.

5.4. Building a Data Warehouse based on Risk Data

There is a need to use data architectures, Management Information Systems (MIS) and Information Technologies (IT) to support the management of risks that companies are exposed to (BCBS, 2013). Constructing a data structure will help to improve judgements on risks. Today a high variety of high-quality data can be collected via different sources such as ERP systems, global markets, social media, etc. (Haksöz, 2013). This data stream directs companies to use effective methods to collect, store and manage this diverse set of data. Effective implementation of risk data management will enhance risk management and decision making processes. Risk data must be both at the business/sector and company level. Risk data may also be gathered from outside/public sources such as insurance companies and local agencies (Knemeyer et al., 2009).

The aim of this part is to develop and build a subject-oriented and integrated data warehouse and extract risk data marts from this data warehouse in order to use in the

DM applications of the proposed model. Risk Data Warehouse (RDW) is the central repository of integrated risk data from different data sources. It can be seen as the corporate's risk memory. RDW stores both current and historical risk indicators in a single repository. RDW provides the opportunity of analytical processing of the risk data stored in the data warehouse. DM module is integrated with the RDW to provide a systematic and interactive data analysis platform.

RDW provides the capability to track and monitor risk factors over time (Berry and Linoff, 2004). It is one of the core steps of the proposed model. Waterfall methodology is widely used for building data warehouse systems (Royce, 1970). Various variations of the traditional model have been proposed and used for building systems. We adapted the Waterfall methodology in the book of Rainardi (2008) to develop a RDW as in Figure 5.4. There are ten basic steps for the development and deployment of a RDW. These steps should be performed iteratively. Each step is explained in the following.

i) Perform a feasibility study: A company may adapt its data warehouse to include risk data and gather a data mart for the DM application from this data warehouse, or it can prefer to develop a separate RDW for its company. The choice of the company depends on various issues including: variety of risk types, risk exposure level of the company, volume of risk data, frequency of risk problems, and the budget of the company. Small companies may prefer to use data marts because of the high costs of data warehouses (Prenhall, 2017). Estimating the duration and cost of the development of a data warehouse requires experience in this area (Rainardi, 2008).

ii) Identify risk indicators and determine the sources of risk data: Data related with different risk factors and a set of risk indicators are identified in this step. Data requirements are determined by considering the results of the risk identification step. Selected risk indicators and other related data will be used in the identification, assesment and monitoring of risks and detection of new risks. Risk indicators help us to identify risk events and track the changes in risk exposure levels (Scarlat et al., 2012). This step has a critical effect on the success of the DM-based SCRM model. There are thousand of risk indicators that are used to measure, assess and track risks (Scarlat et al., 2012; Protiviti, 2014; Chapelle, 2015). Identification of risk indicators varies according to the industry and the enterprise. Identification of risk indicators

requires a high level of expertise in SC risks and information about the focal company. It requires a collaborative study of people with different background and expertise. Risk indicators related with a function of the company should be determined by a cooperative study of different departments. For properties of good risk indicators we refer to Section 4.3.

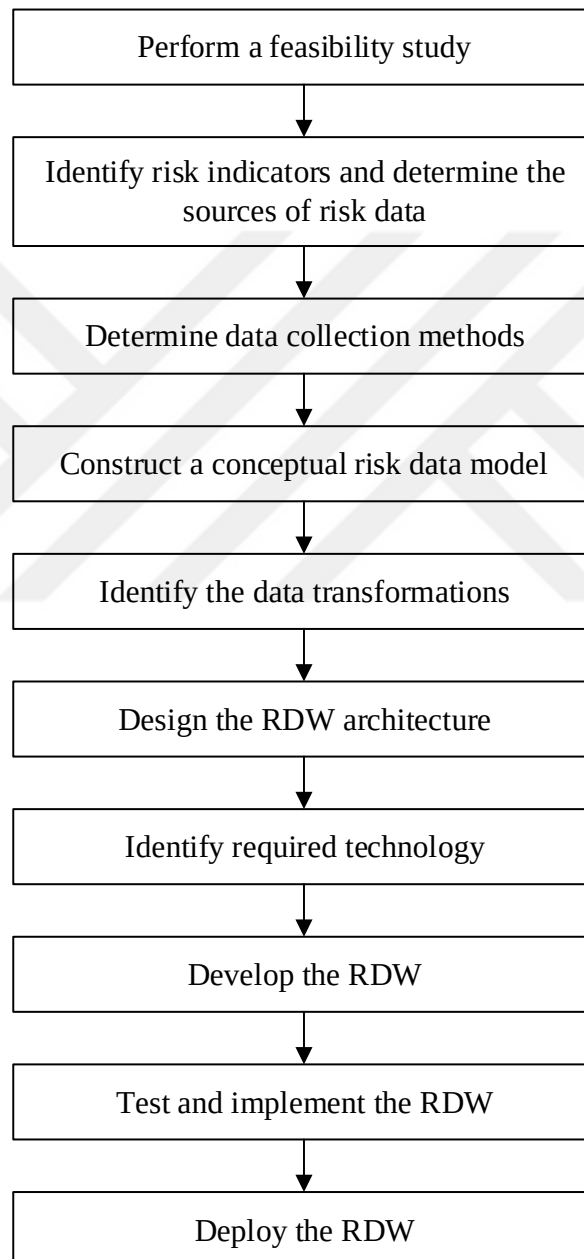


Figure 5.4. Main Steps of the Development of a Risk Data Warehouse (adapted from Rainardi, 2008)

The number of the risk metrics effect the efficiency of the SCRM system, hence a manageable number of risk metrics should be selected by the risk analysis and management team (IOR, 2010; Scarlat et al., 2012). While a high number of risk metrics will take a very long time, an insufficient number of risk indicators will prevent to gain sufficient information about risks. The following questions should be considered while determining risk indicators;

- i) What do we want to measure by using this risk indicator?
- ii) How can the selected risk indicator(s) be used in the identification, assessment, monitoring or detection of risks?

iii) Determine data collection methods: Risk data may be quantitative or qualitative in nature. While some of the risk data can be gathered directly from operational or external databases, some of the risk data can be gathered by qualitative data collection methods and manual data feeds. There are various data collection techniques and procedures. Some of these techniques that can be used to gather risk related data or quantify risks for DM applications are listed in the following.

- **Gathering risk data from operational databases:** Risk data may be collected from various operational databases including purchasing database, production database, customer database, etc. (Prenhall, 2017). Operational risks constitute an important part of the risks in SCs. The data associated with these risks (operational risk indicators) are generally gathered from operational databases (MS, 2014). Enterprise Resource Planning (ERP) systems collect, store and manage company wide data, hence risk related data may be gathered from the ERP database (Neef, 2005).
- **Gathering risk data from external databases:** Risk data may also be gathered from external databases provided by consultancy agencies, insurance companies, commercial providers and, local and international consortiums (Franzetti, 2011; MS, 2014). Global Operational Risk Loss Data (GOLD), Operational Risk Data Exchange (ORX) and American Bankers Association (ABA) are three examples for data consortiums in the banking industry (Franzetti, 2011; MS, 2014). Other external data examples are geographical location data, real time data associated with natural disasters (e.g. earthquake, flood, hurricane) and weather conditions

provided by external information providers (Goh et al., 2013).

- **Gathering expert opinions on risks by using qualitative data collection methods:** Expert opinions, views, experiences, assessments and ratings on risks can be used to gather data about the current risks, their triggering factors, likelihood, consequences and detectability levels. Some of the data collection methods that can be used for this purpose are interviews and surveys (questionnaires) (Gill et al., 2008; Fowler, 2014).
- **FMEA:** This technique can be used to gather data about the likelihood and consequences of different risk factors (Chen and Wu, 2013). A typical FMEA table for risk identification and assessment includes the following columns: risk factor, potential failure modes, priority of risk, severity of risk, risk priority number, recommended risk management actions and responsible staff (Sinha et al., 2004). A risk priority number is calculated by multiplying probability and severity of the risk. Some researchers also incorporate the likelihood of being detected either before or after they occur for risk assessment (Bradley, 2014).
- **Value-at-risk (VaR) and Conditional Value-at-risk (CVaR) methods:** These methods may be used for the measurement and quantification of SC risks. Value-at-risk is a statistical tool that measures the level of risk exposure at a given confidence level (Fang et al., 2016). Conditional value-at-risk evaluates the probability that a specific loss will exceed the value at risk threshold (Sawik, 2011; Sawik, 2014). While value at risk is used to measure high frequency - low impact risks, conditional value at risk is used to assess low frequent - high impact risks.
- **Simulation:** Simulation is an analytical model that imitates a real-world process. A very large number of scenarios can be generated for different values of uncertain parameters from probability distributions (Arıkan, 2005). A distribution is selected to represent the unknown parameter and parameters are identified by experts. Simulated data can be used to discover hidden sources of risks, analyze the patterns of different risk factors, examine the relationships between risks and their triggering factors, and analyze the impacts of risks (Brandt et al., 2012). The success of simulation depends on how well the actual system is explained by the simulation model.

- **Use of monitoring devices to collect risk data:** Technological devices may be used to track items or determined metrics such as temperature, pressure, etc. Monitoring devices include RFID systems, sensors, cameras, motion sensors, wearable devices, energy monitoring systems, etc. (Fugini et al., 2016). These technological devices may be; i) set up in a specific area: e.g. cameras or thermometers in the warehouses, energy monitoring systems that are used to view electricity usage, ii) attached to resources or products: e.g. time and temperature monitoring devices attached to food or medicine, iii) hold by people or attached to a person: e.g. barcode hand scanners, RFID readers, etc.

SCRM has to deal with larger amounts of data load today. Increases in the variety, scope, scale and volume of data generated by SC operations drive companies to use big data concept in SCM and SCRM. Organizations started to mention from big data era instead of data (Oktay Firat, 2015). Especially financial organizations have to deal with very high volumes of credit risk data.

Organizations should collect accurate and up-to-date data on risks. The frequency of risk data updates is an important factor that changes according to the risk type and the industry of the company. As an example, the estimations about floods should be updated periodically because of the seasonal effects on this type of risk (Knemeyer et al., 2009). However, timely data is important for some critical risk factors.

iv) Construct a conceptual risk data model: The data of an organization are stored in operational systems to perform regular operations in different departments including sales, production, customer service, etc. The data related with risks (determined risk metrics) are transferred by ETL process and organized in the RDW (Prenhall, 2017). The data are organized by their sources to create a relational data source. The RDW is used as a central repository of information about SC risks gathered from multiple databases. The purpose of developing a RDW is to make risk related data accessible, appropriate and ready for DM. Data warehousing gathers and stores data from various sources in a common and consistent format (Berry and Linoff, 2004).

The RDW also includes information about the source of information for each risk indicator and the responsible department or person for the supply of this data (IOR, 2010). Risks may be defined by using their different attributes. A set of predetermined

attributes of each identified risk should be determined and stored. These attributes may include location of the risk, source/ triggering factors, probability, consequences, duration and owner of the risk (Kayis and Karningsih, 2012). An example star schema for risk data model is represented in Figure 5.5. Risk data model is built according to data source. The identification of the risk data structure depends on the key risk factors, the structure of the company, data analysis requirements and choice of the risk data analyst.

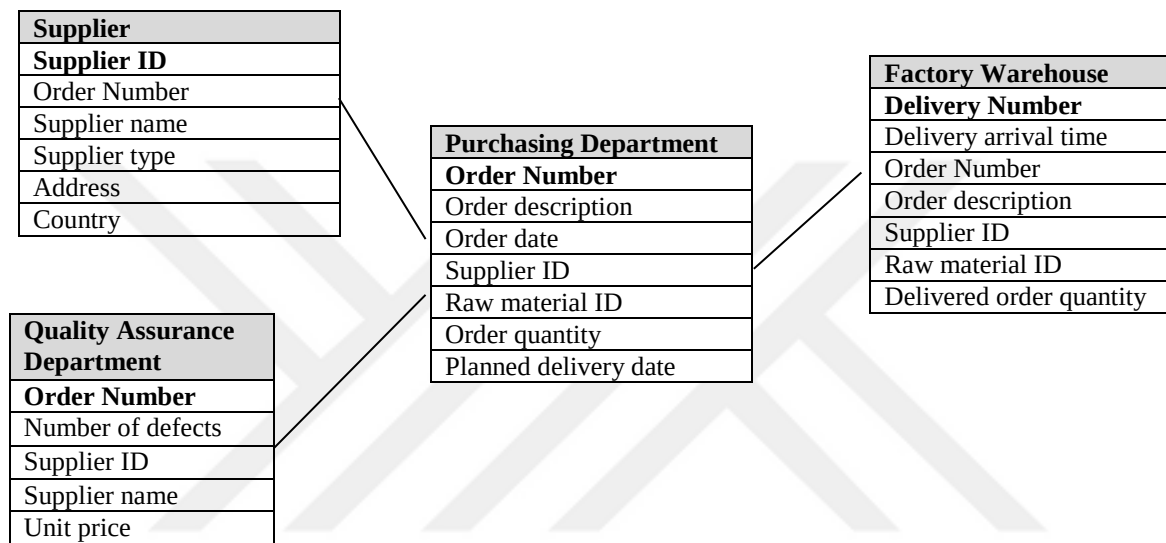


Figure 5.5. An example star schema for risk data model

A specific type of risk or risk area is selected for the DM application. The risk data is pulled from the RDW by the risk type. The risk indicators associated with identified risk type are listed for the DM expert to assess the required metrics for the selected DM application. This relationship between risk type and risk indicators is stored in the metadata layer.

v) Identify the data transformations: After the creation of a risk data model, the next step is the transformation of this model to a data warehouse data model (Silverston, 2001). There are various types of transformation processes. Some of them can be listed as follows: generating composite risk indicators from risk related data, formulations, merging different risk data from different sources, extraction of unnecessary data, etc. (Rainardi, 2008; Silverston 2001). This step is very important for the development of a RDW because risk factors are generally quantified by performing some transformation

procedures; e.g. calculation of delivery delay by taking the difference between the planned and actual delivery time.

vi) Design the risk data warehouse architecture: This step includes the design and the specification of the data sources, staging, ETL system, data flows, data storage, metadata, front-end applications and presentation layer of the data warehouse (Rainardi, 2008). The data source layer of the data warehouse includes the different internal and external sources of risk data that will be utilized in the RDW. Risk data are gathered from the data sources to the data warehouse in the data-staging phase. Data related with risk factors are extracted from the operational databases or external sources through the ETL process (see Section 4.1). The data is transformed to an analytical structure in the ETL layer. The following issues should be regarded while choosing the suitable ETL tool: i) data volume, and ii) complexity of data transformation (Doruk, 2017; Pamuk, 2017). It is one of the most time-consuming activities in developing a data warehouse. Data storage layer includes the transformed and cleansed risk data.

The data warehouse also contains metadata that is data about data (Prenhall, 2017). The metadata in the risk data warehouse includes summaries of risk data (risk data index) and rules for the organization of the risk related data. Metadata layer is very important for the DM-based SCRM model, because it includes various information about risk indicators and can be seen as a roadmap to access the risk data. Metadata includes source of data, related risk factors, location of the risk (e.g. business process such as ordering, supplier selection, and shipping), owner of the risk and, data collection frequency and methods. Table 5.1 represents an example table for the representation of metadata contents. Description part includes a brief explanation about this data. It may include the calculation of a risk indicator. Relevant risk(s) part refers to the risk(s) that the current indicator can be used to measure, assess and track. A risk indicator may be used to analyze more than one risk type. Type of data states whether the data is qualitative or quantitative. Source of the data may be a department, a responsible person or an external data source (IOR, 2010). Risk data may be collected on real time or periodically (e.g. monthly, quarterly, yearly, etc.). The responsible department/person for the collection of this risk indicator is also stored in the metadata repository. Knowledge mapping may be used in the identification of the responsible people for different risk types and data.

Table 5.1. Metadata contents

Information about risk indicator	
ID:	
Name:	
Description:	
Relevant risk(s):	
Calculation method:	
Type of the risk data:	
Source:	
Collection time:	
Responsible department / person:	

The quality of the data is very important for the success of the DM application. An appropriate design of databases and data entry applications reduce wrong, missing, empty or duplicate data problems (Rahm and Do, 2000).

The RDW should also include information about past risk events, previous risk analysis studies and risk management actions, since the experience gained with the past information is very important to select effective risk management strategies.

vii) Identify required technology: The physical infrastructure of the RDW is identified in this step (UCT, 2010). The following issues should be specified: storage area, database server, ETL server, hardware platform, network topology, required software, client computers and user interface (Doruk, 2017; Pamuk, 2017). The following issues should be considered while choosing the right hardware: i) scale of the data (amount of data flow, storage needs, etc.), ii) budget of the company for this area. The performance of the RDW and hence DM-based SCRM model is highly dependent on the physical infrastructure of the data warehouse system.

viii) Develop the risk data warehouse: This step includes the development of the designed parts. Physical linkages are carried out between elements of the risk data warehouse architecture.

ix) Test and implement the risk data warehouse: The configuration management is implemented in this step.

x) Deploy the risk data warehouse: Data are extracted from internal and external databases to the risk data warehouse.

The success of the DM-based SCRM model is highly dependent on the identification of the true risk indicators and development of an efficient and accurate data warehouse.

5.5. Analysis of the Risk Data by Data Mining Module

This section presents a general architecture to convert risk data to risk information and knowledge with the help of DM tools and techniques. Risk data is meaningless until it is subjected to data and information processing. Risk information refers to the facts about a risk factor, in other words it consists of risk data to which a meaning has been given (Doyle, 2000). As an example; the delivery dates of suppliers form a data set, but the percentage of late deliveries by a supplier constitutes a risk information. The association between number of late deliveries and other factors is a risk knowledge. Risk knowledge is required to decide risk management decisions.

Raw data about risks is extracted from various internal and external databases and loaded to the data warehouse. A data mart is created from the RDW for the current DM analysis. Data mart level is sometimes called departmental data level by researchers (Inmon, 2005). In the DM-based SCRM model, the data mart that is subject to DM algorithm is called a risk data mart. Risk data mart (risk problem database) is a subset of the RDW and created from the RDW by transforming, summarizing and shaping the data according to the requirements of the DM application. Risk data is gathered from the server by the DM module. Figure 5.6 summarizes this process and the relationship between RDW, risk data mart and the DM part. As it is seen from the figure, the DM-based architecture is used to convert risk data to risk information and knowledge. Risk wisdom may also be added as an extension to this framework. Risk wisdom is created by embedding the experience, beliefs, perspectives and understanding of the experts to the risk knowledge.

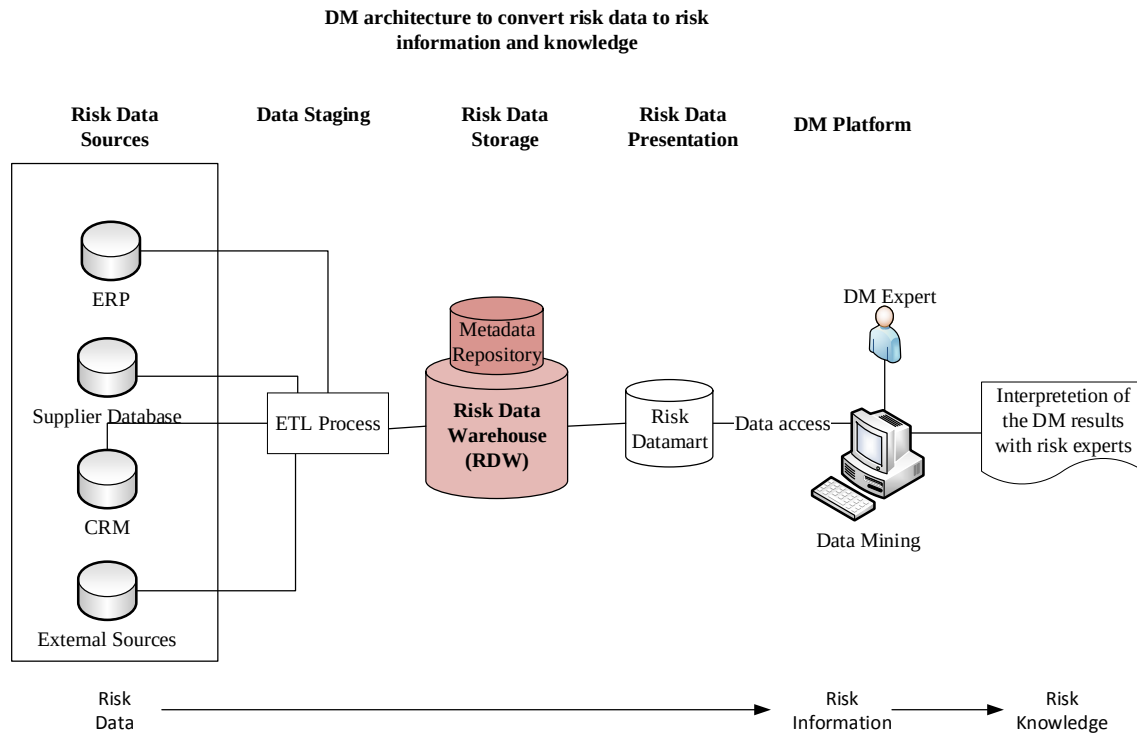


Figure 5.6. A general DM-based architecture to convert risk data to risk information and knowledge

After the development of a RDW, the **DM expert interacts** with the DM module during two steps: i) Determination of the DM application, and ii) Interpretation of the results. The interpretation of the results of DM constitutes the risk knowledge required for the SCRM actions. Figure 5.7 presents an overview of the DM process in the proposed model.

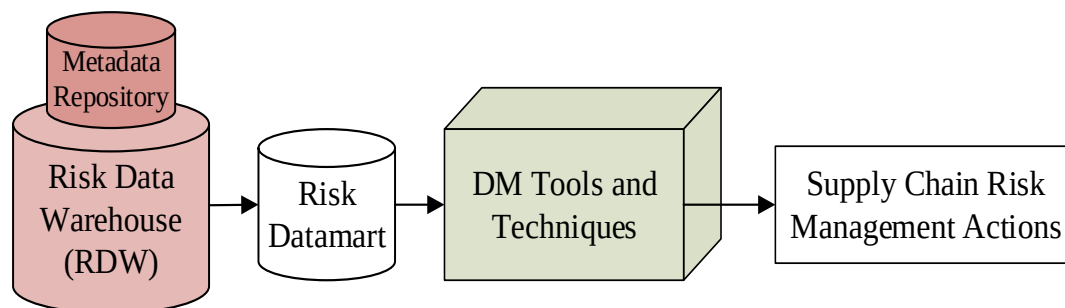


Figure 5.7. Overview of the data mining process in the proposed model

DM module contains a multistep process from the identification of the application domain and the interpretation of the results. The steps of the DM module are explained respectively in the following.

Step 1- Identify the risk management problem and objectives: The first step of any analysis is to define the research problem and aim of the analysis (Hair et al., 2006). Hence, first a risky SC process and the key risk(s) this process is exposed to are determined. Then a risk analysis and management problem is identified and defined by the risk management team. The selected risky SC process and the identified risk factors will be the focus of the DM module.

Step 2- Translate the risk management problem into a DM problem: After the identification of the SC risk problem, the next step is the translation of this problem into a DM problem. “Translation of the business problem into a DM problem” is the first step of the DM methodology proposed by Berry and Linoff (2004). We refer to Chapter 3 in their book for additional information about this transformation process.

In the DM-based SCRM model, this step includes the identification of the DM task based on the previous step. The selection of the DM task should depend on the expected output and the needs of the solution. The identified DM problem and its specific and tangible objectives should be clearly identified in this step. A clear, sufficient and accurate definition of the problem and its aims is a key step that affects the accuracy and effectiveness of the DM application (Giudici and Figini, 2009). The results of the DM method will be used to assist in solving the identified risk management problem. Most of the risk problems may be formulated and solved by using the tasks that can be performed by DM tasks (See Section 4.1 for detailed information about DM tasks). Each DM task has its own functionality. There are various DM tools and techniques that may be used in analyzing risk data such as association analysis, classification, clustering, anomaly detection, decision tree, NN, etc. (see Sections 4.1 and 4.2 for detailed information).

Determination of the framework of the DM application is one of the most crucial processes of the proposed model. Problem formulation step of a DM process includes the identification of the information requirements that will be supplied with DM

(Feelders et al., 2000). Different DM-related questions may be asked in this step. Some examples are determined and listed for the SCRM area in the following:

Question 1: How can we find the factors that lead to risks?

Explanation: This question is related with the identification of the triggering factors of risks. Association analysis, regression, classification or decision trees can be used to discover different factors that lead to risks.

Question 2: How can we model/ predict a risk factor?

Explanation: This question searches for a way to build a model for the prediction of a risk factor. Different DM tools such as regression, decision tree, classification, time series analysis and NN may be used for this purpose. The risk management team may prefer to predict the value of a risk factor; e.g. demand volatility or they may prefer to predict the risk exposure level of a stakeholder; e.g. predicting the risk levels of new customers.

Question 3: Is there a relationship between risk factors?

Explanation: There is a relationship between different risk factors (See Sections 3.1 and 3.2). A risk expert can demand to examine the interrelationship between different risks. Association analysis can be used to discover the interesting relationships within large databases.

Question 4: How can we characterize different items, processes or SC stakeholders based on risk?

Explanation: This question refers to find a way to characterize and summarize different items, products, processes, SC stakeholders or market zones according to their risk exposure levels. Some specific example questions are listed in the following:

- i) How can we characterize suppliers according to their risk profile (e.g. in terms of late delivery, low quality products, low reliability, etc.)?
- ii) How can we characterize the suppliers that have high delivery risk?
- iii) Which groups of suppliers tend to create higher risk?
- iv) How can we characterize the customers according to their risk profile? / How can we create a profile of risky customers?

- v) How can we characterize the risky products?
- vi) How can we characterize the risky processes?

Clustering can be used to group different stakeholders (e.g. suppliers, customers, etc.), products or market regions according to their risk profile. For example; a market can be clustered based on the characteristics of different regions such as exchange rate, terrorism, disaster, GDP, etc. Alternatively, a classification model can be developed if the risk management team wants to assign different items or stakeholders into different risk classes based on pre-determined attributes.

Decision tree method can be used to classify suppliers/customers based on their risk profile. A decision tree derives the rules to classify existing suppliers/customers (Berry and Linoff, 2004). The results of the decision tree may be added as a new attribute to the supplier/customer database.

Question 5: How can we detect unfavorable variations in risk factors?

Explanation: DM algorithms can be used to discover unfavorable patterns for selected risk factors. This process can also be used for the purpose of an early warning system for risks.

Question 6: How can we detect anomalies within a data set?

Explanation: This question is related with the detection of anomalies, abnormal values, outliers, errors and frauds within data sets. Anomaly detection is frequently used in financial risk assessment in the banking sector.

Feelders et al. (2000) also provides different question examples for the formulation of the DM problem. These DM related questions will be the basis of the goal of the analysis. Besides, decision makers should also decide how to use the results of these questions (or DM) in assisting risk management decisions (Berry and Linoff, 2004). This decision is important for the effectiveness, practicality and accuracy of the DM problem formulation.

Step 3- Identification of the risk indicators and required data for the DM problem:

A RDW is created to store the risk-related data and previously encountered risk factors with the solutions applied to manage these risks in Section 5.4. This step includes the identification of the risk indicators and other required data to accomplish the determined

DM application. The data needed for the identified DM problem is extracted from the RDW and data mart. If the collected data is sufficient the decision makers continue by selecting and specifying the appropriate DM tool and algorithm based on the structure of the data set. If the data is not sufficient, the decision makers try to identify and collect additional data for the DM application. The following question should be answered while determining risk indicators: “Does this indicator help to identify and measure an existing risk factor?” (IOR, 2010).

Step 4- Examine/analyze the collected data: This step includes the analysis of the collected data including general statistics about the data, number of missing values, etc. This step aims to provide information about the data distribution and relationships between risk indicators. This preliminary information about the risk related data helps to understand different risk indicators and select the appropriate DM technique. Data visualization tools such as charts, graphs, maps and dashboards can be very helpful in this step (Berry and Linoff, 2004).

Step 5- Measure and quantify risks: The selected risk related data may be directly used as an input in the DM algorithm or it can be used to measure a risk type. Different data may be used to quantify a specific type of risk by a determined formulation. In addition to quantifiable risks, qualitative risks may also be used by using expert opinions or judgements. Quantification of these risks is also another decision point in the model. This is generally determined before the data collection process; e.g. preparation of questionnaires.

Step 6- Select a specific DM task and technique: The selection of the DM techniques and algorithms for the selected DM task is another decision point. There is not a DM tool that can be applied for all of the DM tasks, hence the most suitable technique or algorithm should be determined for each of the determined DM problem by regarding the structure of the available data. The selection phase of DM algorithms may be strengthened by developing an expert system or a decision tree model (Gargano and Raggad, 1999).

DM algorithms may also be selected from a DM library that is created during the development of the DM-based SCRM framework in the company. This library should

be updated by the DM expert based on the requirements of the company and the structure of the SC data.

Step 7- Specifying the DM algorithm(s): After the identification of a specific DM technique, the decision makers need to develop an analysis plan including the details of the required risk indicators, sample size, type of measures, variable formulations and specific details related with the selected method (Hair et al., 2006). The data analysts may also prefer to apply different techniques and select the most appropriate one by comparing their performance.

Step 8- Identification of the DM software: The company may choose to buy a third party DM tool or to build the DM tool according to their needs. The cost, development time, staff and technical capability of the company should be regarded in this decision. There are various commercial DM software products. Professional (vendors; such as SPSS and SAS) and open source (free download; such as RapidMiner, Orange, Statistica, Weka) software packages can be used for the analysis and application of DM algorithms. The selection of the software depends on the characteristics of the data (size, dimension, etc.) and the DM algorithm.

Step 9- Preparing the risk data for analysis (Preprocessing): Risk-related data is extracted from different and heterogeneous operational and external data sources. Hence, the data have different formats and types (e.g. text files). In addition, there may be noisy and missing values. Therefore, data must be preprocessed before applying DM algorithms. Selecting the data and pre-processing are the most time consuming activities (Feelders et al., 2000). Data preprocessing includes various procedures and some of them are explained in the following (Malhotra, 2007; Han et al., 2012):

- **Data cleaning:** Risk related data comes from various distributed and heterogeneous data sources. Hence, a data cleaning process is required before integrating these data. The noise is removed and missing data is supplied or estimated in this step.
- **Data integration:** Various internal and external data is used for risk analysis. Risk related data is stored in various forms and structure. Data integration is combining the data from different sources and providing a unified view of data for using in the DM application. If the company prefers to develop a data warehouse, data

integration process is generally implemented in the development of the data warehouse through specialized software.

- **Data transformation:** In the transformation step, all collected data should be converted into a common/single format for processing the DM algorithm. Some data may be combined to obtain a new risk data variable; e.g. multiplication of the severity and probability of a risk factor to obtain a risk priority number. Categorical variables may be grouped under different classes, transformations such as logarithms can be performed or counts can be converted to proportions, etc. (Berry and Linoff, 2004). As an example, the number of defective units from a particular supplier can be a misleading risk indicator, because the amount of the supplied units vary according to suppliers. Hence, this indicator may be divided by the total number of supplied units from the supplier and converted to a new risk indicator; the percentage of defective items for a specific supplier. DM algorithm is applied on the transformed data.
- **Data reduction:** This process may be used to eliminate duplicate records, removing redundant data or data compression to reduce the data storage capacity. Dimensionality reduction is one of the most common techniques in this area. It can be applied to decrease the number of risk related variables before applying the specified DM algorithm.
- **Data filtering:** SCs include a huge volume of data. However, the company may prefer to apply the DM tools and techniques in a specific subset of the data. Therefore, a data-filtering step can be required based on the risk area and DM problem.

Step 10- Performing the DM process: The selected DM algorithm(s) is performed on the preprocessed risk data to achieve the determined DM goal. This step is performed by a DM software or a DM module integrated to the information system of the company.

Step 11- Validation of the DM model: The selected DM model should be validated by the DM experts before the interpretation of the results by the risk management team. The selected DM technique may be compared with different techniques to ensure its validity (MS, 2014). Different properties may be used for this comparison such as explanatory power, accuracy, speed, robustness, amount of preprocessing needed and

ease of integration (Gargano and Raggad, 1999). A sensitivity analysis may also be performed in order to examine the sensitivity of the model to changes in risk indicators.

Step 12- Interpretation and evaluation of the results of the DM algorithm: This step includes the interpretation of the results of the selected DM analysis in order to assist in deciding risk management strategies.

5.6. Interpretation of the Results of the DM Module

DM module provides real time and useful information about the selected risk factors by analyzing the risk-related internal and external SC data. DM-based SCRM model is interested in past, current and potential risks. It provides historical, current and predictive views of risks as in Lee and Kulkarni (2011). The results of the DM algorithm is used as an input of decision making process for SCRM. Interpretation and evaluation of the results of DM algorithm(s) provides the transformation of risk information to risk knowledge. DM may provide the following types of information about risks:

- i) Prediction of risk events: DM may be used in predicting different risk events with respect to various factors by using past data. Examples include forecasting bankruptcy, customer churn, demand volatility, machinery or equipment failures, etc.
- ii) Discovery of risk patterns: Patterns in exchange rates and traffic conditions are examples of this type of information.
- iii) Association among risks and between risks and their triggering factors: Association analysis may be used to discover the factors that may lead to risks or to find the relationships between different risk factors.
- iv) Classification of different items according to risks: Classification may be used to assign different items, objects, suppliers, and customers to predetermined groups. Examples include classifying new customers according to their risks.
- v) Clusters of different items based on risk factors: Clustering may be used to group items that have similar risk characteristics. Clustering analysis may be used to group products, customers, market regions, processes or suppliers according to their risk profiles. As an example, suppliers in bad locations may form a risky group in terms of transportation risks.

- vi) Summarization of risk data: Databases may contain huge amounts of risk related data. Hence, risk analysts may need to summarize the risk data using some characteristics to assist in further analysis.

These outputs of DM algorithms will be used in assisting decision makers in identifying and controlling risk management actions. Risk management team should use the results of the DM module to take informed and effective actions. This step is crucial because the efficiency, success and usefulness of the DM-based SCRM model is highly dependent on the decision of the DM application and the evaluation of the result of the DM algorithm. Visualization tools (Visual DM) may be very helpful in the interpretation of the results. The analysis results may be stored in the risk database for future references.

After the analysis and assessment of risk data, the risk analysis and management team should identify the actions and plans for the mitigation and management of the focused risk factors. There are various alternative strategies and techniques. We refer to Section 3.5 and Er and Oktay Firat (2014) for detailed information for different SCRM methods. Alternative strategies are evaluated by domain experts and risk management specialists by considering various different factors such as cost and benefits. The expected contributions of the countermeasures are important because the cost of a mitigation effort may be greater than the potential loss resulting from the related risk (Knemeyer et al., 2009). After the identification of the risk management activities, a risk mitigation plan is developed to accomplish them. Risk mitigation and management actions are determined due to the risk strategy of the company. Risk attitude of the firm influence the selection of the risk management technique. The results of the risk management efforts should also be measured and evaluated for their validation. The last step of the DM-based SCRM model is reporting the results of the DM application and risk management activities. Risk data and reports help companies to monitor and track risks based on the company' risk tolerance level (BCBS, 2013).

The scope of the thesis covers the steps from the analysis of the structure of the SC to the interpretation of the results of the DM algorithm to assist risk management actions. Therefore, the last steps are beyond the scope of this thesis. For a literature review on SCRM methods, we refer to Er and Oktay Firat (2014).

5.7. Implementation Issues and Additional Notes

Data warehousing constitutes a central repository for risk related data. Analysis of this data by DM tools and techniques provides the intelligence needed to make more informed decisions for SCRM. The key factor to have a proactive risk management is the effective management of the risk related data and knowledge of risk experts. DM is a tool that helps to adequately and accurately assess risk factors and make more informed and efficient risk management actions. The success of the proposed model depends on various steps including the translation of the risk problem into a DM problem and selection of the DM method and algorithm.

The proposed DM-based SCRM model provides the following opportunities and features for SCRM:

- Provides a comprehensive guide to develop a SCRM system utilizing DM tools and algorithms for analyzing risk related data,
- Develop a systematical model to use the increasing amounts of enterprise data to identify, assess and monitor risks in the SC networks,
- Helps to discover hidden and useful information from risk data for the purpose of identifying effective risk management actions,
- Provides decision makers with the information to assist in developing a risk management plan,
- Supports decision makers to make more informed and intelligent risk management decisions,
- Increase the visibility of the SC risks,
- Helps to easily detect risks,
- Provides the opportunity to analyze risky points in the SC processes and the underlying reasons for these risks,
- Helps to gather, store and manage risk data with the help of Data Warehousing and DM tools and technologies,
- Enables analysis and modeling of different risk factors together,
- Enhance the effectiveness of SCRM decisions by utilizing the results of DM algorithms,

- Supports real-time analysis of the risk data,
- Bring new insights to SCRM area.

There are also some limitations to develop and implement the proposed DM-based SCRM model. These issues are listed in the following:

- The input of the DM algorithms is the databases. Hence, if the database does not provide complete, accurate, clear, related and dynamic data, there may be problems in applying DM algorithms or taking accurate results.
- Some of the risk data may depend on subjective evaluations. This is another issue that affects the accuracy of the results.
- The adaption of the DM-based SCRM model depends on the technology in the organization. It may require additional investments for technological infrastructure and workforce to setup the model. The amount of the investment depends on the current technological infrastructure in the organization. Especially IT degree of the company including hardware and software is very important.
- The selection of the DM applications requires knowledge about the company, expertise on risks and an expertise on DM tools and algorithms. Hence, the success of this part depends on the expertise and experience of the risk management team.
- Although development of a RDW is very advantageous, it may require a high cost for the company to build and maintain a data warehouse.

One of the deliverables of the proposed SCRM model is the results of the DM algorithm. It requires a certain level of expertise on DM to comment on these results. DM expert interacts with the DM module during two steps: i) determination of the DM application, and ii) interpretation of the results together with the domain experts and risk analysts. A user interface may be added to the DM module to select and review the relevant risk data, application of the DM algorithm(s) and visualization of the results of DM. A user interface supports the interaction between the DM-based SCRM model and the users.

The data in the risk warehouse is updated from the operational and external sources periodically. A real-time warehouse may be developed to quickly detect potential risk

factors and patterns on risks. The model should maintain real time data in order to have a more proactive structure and react to emerging threats. However, the management of real time data is more difficult due to the required high level of technology and expertise on real time data analytics (Anderson-Lehman et al., 2004).

SCs are dynamic in nature; hence, the status of risk factors may change over time. A monitoring part can be added to the model. Risk factors should be monitored regularly to detect emergence of risks and, track the efficiency of the risk management efforts and strategies. SCs should learn from past disruptions in order to take proactive and preventive actions. Hence, a learning feedback mechanism can also be added to the DM-based SCRM model as in Revilla and Sáenz (2014).

The advances in computing and communication systems have resulted in increased collaboration between the members of SCs. Therefore, it requires monitoring and analyzing different distributed sources of high volume data. DM technologies designed for distributed applications can be very efficient in the distributed computing environments. This property can be very helpful in SCRM systems that have a complex and multi-faceted nature. Finally, big data analytics may also be adapted to the proposed SCRM model. Nowadays, the volume, scale and scope of SC data is growing rapidly as a result of technological developments and increased collaboration and communication between SC partners (Oktay Firat, 2015). Hence, big data analytics has started to gain increasing attention in the SCM field.

There are some important notes that companies have to regard in the implementation of the DM-based SCRM model:

- DM-based SCRM framework is not a one-time process and requires a continuous effort. The developed SCRM model should be continuously monitored and maintained.
- Translation of the risk management problem into a DM problem is one of the most crucial steps of the proposed model. In this step, risk management team should also determine how to use the results of the identified DM application (Berry and Linoff, 2004).
- It is not possible to analyze all of the risk types in the same study. The proposed model requires focusing on a specific risk type and selection of a specific DM

task. Hence, each risk and DM problem may be regarded as a new application/project.

- Development of a RDW may require high costs for the companies. Hence organizations should perform a feasibility study before data warehousing. Instead of building a RDW small size organizations may prefer to develop a risk data mart directly from databases in the company. Data marts are subsets of data warehouses and require lower costs.
- The resources of the company may be inadequate to develop a risk data warehouse or a data mart. In such a situation the company can apply the model by searching the data from operational databases in various departments of the company (Berry and Linoff, 2004). However, the data preprocessing and transformation part will require a high effort.
- If the proposed framework will be used on a daily basis to analyze risks, it should be integrated with the existing information system and data warehouses of the organization.
- Organizations should track technological changes and the developments and innovations in the DM tools and techniques.

6. ADAPTATION OF THE PROPOSED MODEL TO A SELECTED COMPANY

In this section, the DM-based SCRM framework is partially adapted to a company. The steps of the proposed model is applied respectively. Potential DM applications are listed for the company. Supplier risk is selected as a risk problem and cluster analysis is applied as a solution method to mitigate this type of risk. K-means clustering algorithm is applied to cluster suppliers considering their risk profile. The results of the cluster analysis are interpreted to identify risk management actions. The aim of this section is to demonstrate the applicability of the model and discuss the potential benefits to the selected organization.

6.1. Research Design and Methodology

The DM-based SCRM model and its steps is adapted to a company in order to explain and detail the application of the model. Types, severity and frequency of risks vary according to the industry, business and the structure of the company. Also each company has its own risk profile, risk attitude and risks. Therefore, the application part of the study concentrated on one specific company. After meetings with several companies, one of them is selected for the application of the DM-based SCRM model. Initially three meetings have been done to discuss the aim, scope, benefits and work plan of the current study. A series of face to face interviews, meetings, telephone and email conversations, and field observations were held throughout the application part of the thesis. This part took approximately ten months. This case study company is selected for several reasons:

- i) The company has a 29 years of experience in the sector,
- ii) The SC of the company is global in nature, hence potential geographical differences and global risks in the SC network may be analyzed,
- iii) The managers want to enhance its risk management and are willing and open to share data and information about their processes,
- iv) The company has a huge number of suppliers and manufacturing process is highly dependent on the performance of the suppliers,

- v) The company is currently negotiating with Enterprise Resource Software vendors to integrate all of its processes (Human Resources, Purchasing, Production, Research and Development, Sales, Transportation, Finance, etc.) in a single platform. The aim of the company is to have an effective process management, improved performance and hence gain competitive advantage. The application part of the study will enhance this transformation phase with the help of a data driven approach and provide the incorporation of a risk management module to the planned software.
- vi) They have a supportive and collaborative approach for academic studies.

Studies related with the adaptation of the proposed model to a real company have provided the opportunity to integrate practitioner's point of view to the model.

First the company and its SC is examined in order to understand the structure and characteristics of the job and the SC network. Then a risk analysis and management team is created. Different risk factors, their sources and the indicators that can be used to measure these risks are identified. In-depth semi structured interviews and discussions were performed to identify the risks, potential threats and uncertainties observed by the staff in the company. Risks are assessed in order to identify the application area of the DM algorithms. A survey is applied in the company and various risks are evaluated by the respondents. It is not possible to analyze all types of risks and apply all of the DM tools. Therefore, first potential DM applications are listed. Then, a specific risk problem is identified based on the results of the survey and discussions with the managers in the company. Suppliers have a critical importance for the company, hence mitigation of the supplier related risks is identified as the main risk problem. The risk problem is translated to a DM problem.

The proposed DM approach aims to cluster suppliers considering their risk profile. Before cluster analysis, BWM (Rezaei et al., 2015) is applied to identify the weights of the risk criteria that are used to evaluate the suppliers. To the best of our knowledge, this is the first study that applies cluster analysis to group suppliers based on their risk profile and the first study that uses BWM and cluster analysis together. BWM and cluster analysis is applied on real data. The results of the clustering algorithm are used in order to examine the risk characteristics of the suppliers in different clusters and

investigate the relationships between different risk factors. The interpretation of the DM results provide insights for supplier risk management actions. Suppliers with a high-risk profile can be eliminated or supplier development plans can be developed based on the results of the analysis.

There are some difficulties and limitations for the adaption of a DM-based SCRM model for this company:

- i) The workflows in the company have to be revised before the analysis of the risks within the company and its SC.
- ii) The company is currently using excel tables to record the data related with their operations. Determination and access to the stored data takes a very much effort. Moreover, the collected and stored data variety is not very much. Therefore, only risk indicators that will be stored in the data warehouse is identified. The studies that is performed in this chapter will be a basis of a further project that aims to develop a data warehouse for the company. Negotiations are held with ERP vendors, but this transformation period is a complex, hard and long-term project.
- iii) The company has a make to order production system, hence the variety of the risks expand and quantitative data collection becomes impossible in some risk areas.

This thesis will help the company to fill these gaps by identifying risk areas in the SC, analyzing the risks in all processes, determining the required data types to measure risks, assess and monitor these risks, developing a data warehouse structure, supporting the ERP integration phase with management and risk management approaches, and proposing a DM-based SCRM model for the company. Demonstration of the DM-based SCRM model on a real case enables to detail the model, focus on the risk factors that have the highest priority for the company and identify specific DM techniques and algorithms to implement in various SCRM steps.

6.2. Case Study Company

The case study company is in the heavy machinery sector and, supplies products and services to both domestics and foreign customers. It manufactures machinery and

equipment and also establishes complete turn-key facilities for different industries including mining, cement, wood, defense, iron & steel, work machines, energy and ship building industries. The main products of the company are mills, cone crushers and classifiers for mining and cement industry. The company also builds complete ore grinding and crushing facilities. The company supports project design and management, planning, manufacturing, installation, start up, after sales services and spare parts services.

It was established in 1987 and continues its operations in Kocaeli, Turkey. It continues its operations on 18000 m² indoor area on 30000 m² of land. The SC network of the company consists of a production center, a warehouse, a partner company as an internal supplier, external suppliers, customers and transportation assets. The structure of the network is represented in Figure 6.1.

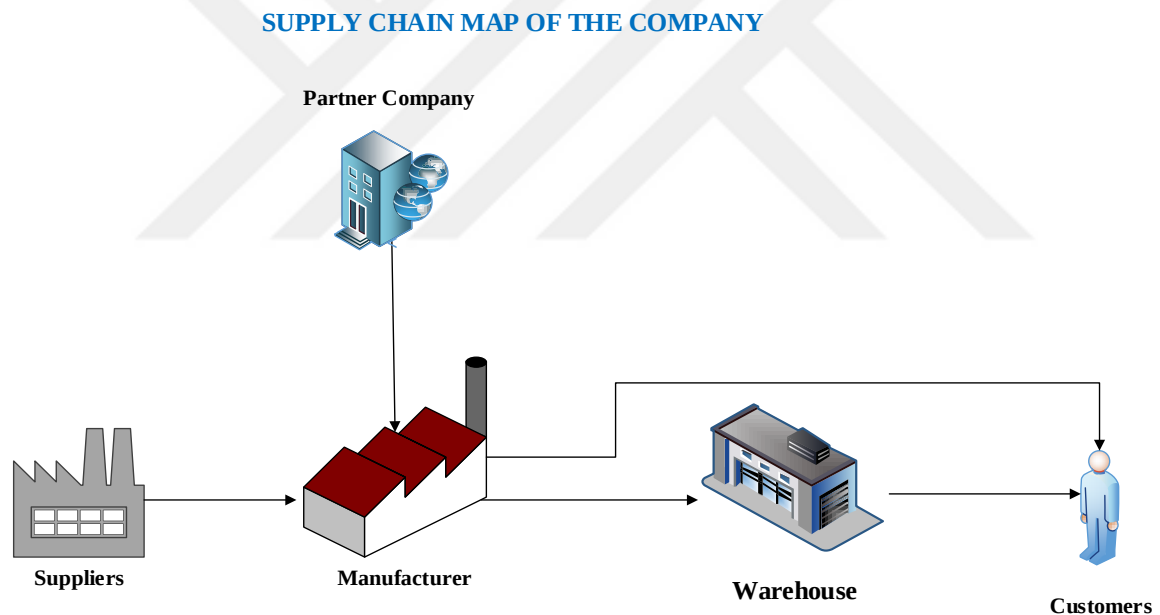


Figure 6.1. Structure of the SC network

The first facility contains the manufacturing of the equipment and parts of the machinery. The second facility, warehouse contains the assembly operations and the testing of the developed product. The second facility will be moved to a larger area closer to the first facility. The construction is continuing. The company has also a partner company in the casting sector. Some of the parts of the ordered machinery and spare parts are manufactured in this subsidiary company. This casting company has a capacity of 5000 tons/year. The single piece casting capacity of the company is

approximately 6 tons. The company produces parts and equipment mainly to the following industries; maritime and shipping, cement, mining, automotive, defense and wood industries. The company exports its products to various countries including Australia and Indonesia.

The focal company has a strong R&D department. While some orders come with technical plans and drawings, in some orders the development and design of the machinery or facility are done by the focal company. The company designs machinery and turn-key plants according to the preferences of the customers and the system requirements. They consider energy efficiency and easy maintenance in the systems they developed. The company has a diverse set of suppliers for different parts and equipment required for the orders.

The market of the heavy machinery has especially requirements on highly customized, quality and reliable products and services. Meeting customer demands and expectations is very important to gain competitive advantage in the sector. Some of the characteristics of the heavy machinery sector may be listed as in the following;

- The market of heavy machinery requires highly customized and configured products and services.
- The industry has a high product variety and dynamic structure.
- Holding stock may be impossible for most of the parts and assemblies because of the high variety in customer orders.
- It may be very expensive to keep inventory.

Manufacturing of the machinery for mining such as mills, cone crushers and classifiers has the biggest share in the company's products.

The company produces highly customized and configured products and hence it uses a make to order production strategy to be more flexible and responsive to the product variability. It has a demand-driven and pull-type production strategy. Each product is produced specifically for an individual sales order. The manufacturing process starts after receiving a confirmed customer order. The product is manufactured according to the requirements and needs of a particular customer. The quantity of the product that will be produced is one or a few. Most of the products of the company has a very long development phase, production time and life cycle.

Some of the properties of make to order production strategy are as follows:

- It allows for an increased level of customization,
- It may take a longer time to fulfill a customer order than in traditional production strategies.
- Production planning is based on orders instead of forecasts.
- It decreases the excessive inventory holding and stock obsolescence problem.
- Each order is tracked separately. Therefore, order status and tracking information is complex.
- The relationships and collaboration with suppliers are critical for the performance of the company.

The production system of the company has to be highly flexible and responsive to cope with the volatility in demand and product variety. Holding inventory is very expensive for the heavy machines. The company should have a proactive demand management system to reduce the inventory related costs. The company should have short lead times, high service levels and reliable delivery times to survive in the highly competitive, unpredictable and uncertain heavy machinery sector.

Customer satisfaction is very important for this sector. Production planning, purchasing, quality control and delivery of the orders may be very intensive and stressful in make to order production environments.

Some of the risks that are commonly encountered in make to order production systems are as follows:

- Uncertain and variable demand,
- Inefficiency in processes,
- Wrong, ineffective or unreliable planning and scheduling (for purchasing, manufacturing, delivery, etc.),
- Delayed deliveries of customer orders,
- Long lead times,

The company faces various SC risks related with demand, production, planning & scheduling, delivery and the structure of the market and sector. Therefore, a robust SCRM system should be developed for the company.

A risk analysis and management team established to apply and develop the DM-based SCRM model. Risk management team contains representatives from different departments and a consultant that is an expert on DM area. This team is developed after several discussion about the roles, responsibilities and background of the staff in the company. The business development engineer in the company has a high level of knowledge on the workflow, job descriptions and risks in the company. Therefore, she is assigned as the risk management director to coordinate risk management studies of the risk management team. Commercial manager of the company has a high level of expertise on the business of the company and the sector. He is a permanent member as a domain expert in the risk management team. A dynamic structure is proposed for the company. Other domain experts will change based on the problem area.

Data management and application of the DM algorithms will be performed by a DM expert (the writer of the thesis). She has an expertise both in risk management and DM tools, hence she will take part both as a risk management expert and DM expert in the team. The case study company outsource its IT services. This company will take the IT expert role in the proposed model.

6.3. Identification of the Risks in the Focal Company and its Supply Chain

Before identifying risks, the following studies are performed in each department in the case study company:

- i) The work that are performed in the department are determined in order to understand the business structure.
- ii) The true definition and documentation of processes enables the employee to systematically perform their activities, test the results and improve the processes. Therefore, the current workflows are revised and new work flows are created when needed.

The mentioned steps are applied in the Sales, Purchasing, Production, Planning, Quality and Human Resources departments respectively. Risk types will vary depending to which processes are being examined; hence, risk analysis is performed by analyzing the functions performed in different departments. The roles of the departments vary by

organization and the type of the business. Hence, first the roles and functions of each department is examined.

The risks and vulnerabilities in the company are identified with interviews, field observations, discussions, brainstorming technique and focus group studies with process owners, business development engineer and managers in the company. The risks that are discovered in the literature review part are used as a guide in determining risks (see Section 3.3). There are various tools and techniques used in determining and analyzing risks. In this study, the identification of major risk areas is performed by performing the qualitative research techniques in Table 6.1. This table represents these studies with the used methodology, its date, aim of the study and participants. Business development engineer who is one of the owners of the company participated to all of the risk identification studies. Each study contains people from various departments, because different risk types are related with each other, and a risk type may have an effect on various business processes. In addition to these studies, field observations are done during ten months.

First, risks are determined under each department. However, some of the risks could not be classified under a unique department; hence, both internal and external risks are grouped under different functions performed in the company. Before introducing the risks, the related department and processes are explained briefly in order to understand the related workflow. At the end of these risks, some of the catastrophic risks and deliberate threats are explained under a separate heading.

I) Risks associated with sales and marketing functions: Sales and marketing department is responsible for the following functions; i) market the products, ii) develop sales plans and strategies, iii) implement the sales protocol appropriate to the type of the order: machinery, complete plant or spare part, iv) providing after sales services, v) managing customer relationships, vi) analysis of the market. The risks and problems in sales and marketing processes should be identified and removed in order to increase sales and customer satisfaction levels. Various factors may threat the performance of the sales and marketing processes. A root cause analysis is done for the following risks that threat the processes in sales and marketing department of the current company: i) low customer satisfaction, ii) poor sales performance, iii) customer related risks, and iv)

market risk. Risks related with the sales and marketing function are explained under two different parts: sales related risks and market risk.

Table 6.1. Qualitative study that is performed to identify risks for the company

Date	Methodology	Aim of the study	Participants
December 14, 2016	Meeting	Gain information about i) Company, its business, customers and the sector ii) Risks in the sector	Commercial manager
December 19, 2016	Observation	Understand the business structure and work flow in the company and observe risk areas	Business development engineer and commercial manager
December 26, 2016	Discussion	Examine the internal and external risks for the company	Business development engineer
January 2, 2017	i) In-dept semistructured interview ii) Brainstorming	Identify sales and marketing risks	Business development engineer, sales and marketing department and commercial manager
January 9, 2017	i) In-dept semistructured interview ii) Brainstorming	Identify the supply related risks and logistics risks	Business development engineer, purchasing department, sales staff and quality insurance staff
January 16, 2017	i) In-dept semistructured interview ii) Brainstorming	Identify the risks related with research and development activities and product/ project design	Business development engineer, research and development department, sales staff and purchasing staff
January 25, 2017	i) In-dept semistructured interview ii) Brainstorming iii) Focus group study	Identify the financial risks and human resources risks	Business development engineer, accounting department, human resources department and general manager
January 30, 2017	i) In-dept semistructured interview ii) Brainstorming	Identify the risks related with production and production planning	Business development engineer, Production planning department and quality insurance department

Sales related risks include the following risk factors:

- i) **Customer dissatisfaction:** The company may gain competitive advantage by providing the customers the true products in an acceptable time. There are various factors that influence the satisfaction level of customers.
- **Information flow risk:** This risk category includes the wrong, incomplete or inadequate information flows from customers to sales office or from sales department to research & development or production departments. The company has a make to order production strategy, hence accuracy of the data on customer orders and the clarity of the definition of requirements are very critical for the company. Sales department acts as a bridge between customers' needs and requirements and the production department. Understanding and documenting the customer needs, requirements and expectations properly is very critical to gain customer satisfaction. The true documentation and transfer of the order information to R&D and production department is also vital for the accuracy of the design and production processes.
 - **Failure projects:** Produced machinery are tested in the factory before their shipment. Then the company performs the assembly and installation processes locally with its project team. The project team delivers the project after performing performance measurement studies and gives the performance report to the customer. As a summary, the company does not deliver a failure product. However failures in the machinery or plants after installation cause customer dissatisfaction, and extra service and repair costs.
 - **Low performance of sales team:** The efforts of sales team has a huge impact on customer satisfaction level. Sales representatives are the first people that contact with customers in the company. Misunderstanding of customer needs and expectations, failure to reach sales representatives when needed, poor or negative communication with customers, and inefficiency of after sales services in terms of response time, response quality and problem solving capability.
 - **Low service levels:** The case study company produces machinery and equipment or establishes complete turnkey facilities for different industries especially to mining industry. A machinery malfunction and the disruption of production cause big amounts of financial losses for customers. Hence after

sales service has a critical importance and the company have to respond to customer breakdown notifications immediately. Low service levels cause to both customer dissatisfaction and bad reputation.

The products/ projects of the company have a 2-year warranty. The details of maintenance, warranty conditions and after sales services should be specified in sales contracts.

- **Communication failures:** A good communication is important to meet customer requirements. Ineffective, inadequate and unclear communication with customers, lack of communication standards, and unavailability of the contact person lead to customer dissatisfaction and damage relationships with customers.
 - **Reliability problems:** Customers expect the company to supply the products or services with the desired quality and specifications in the promised time frame and to solve the problems when needed. Reliability problems may damage relationships with customers, cause customer loss and also threat the brand image. Reliability risk is especially important for the company because of its make to order strategy and high cost products.
 - **Customer relationship risks:** Relationship with customers is very important for companies that use make to order strategy. Inefficient and weak relationships cause failures in project design and manufacturing processes and hence lead to customer dissatisfaction.
- ii) **Poor sales performance:** It may result from various reasons including sales procedure and process related problems, customer disruptions, low performance of sales team and wrong strategic decisions. The company should analyze the reasons for lost sales, canceled/rushed orders, and decreases in revenue. Accurate, reliable and timely information about sales activities helps to detect risks and missed opportunities and, act quickly to solve problems.
- **Inaccurate or inefficient sales procedures:** Inaccurate or inefficient planning and description of sales procedures lead to faults in sales activities. There is not a detailed and up to date flowchart and description of the sales processes. In addition, the job definitions of the staff is not documented. Hence, the sales and marketing staff perform the processes based on their experience and knowledge

on the job. These issues may result in incorrect or missing processes. They may also cause to a big problem when the responsible people quit or become fired.

- **Information system failures:** The information about orders are collected and stored in both printout and excel files. The sales staff may enter a wrong value or change a cell by mistake easily. Excel sheets contain many complex data. Hence, it is very easy to make a mistake and also it may be difficult and time-consuming to reach the information about an order and track the status of orders. In addition, the collected information about orders is not sufficient. All of the mentioned issues are related with the inadequacy of the information system.
- **Contractual risk:** The contracts should describe the expectations from the company in detail. The contracts should cover technical details about the product (properties of the product, desired quality level, loudness level, compliance with environmental standards etc.), cost of the project, payment terms, the scope of the business and responsibilities of both the company and its customer, warranty period and conditions, service and set up/installation costs, installation time, supervisor time according to the characteristics of the region, delivery time, delivery type, delivery point, packaging and delivery details etc. Deficient issues and wrong values create risk for the company.
- **Low performance of sales team:** The performance of sales team has a huge impact on the success of sales activities and sales performance of the company. Sales staff is responsible for analyzing the sales data, performing manufacturability and pricing studies, gathering information about customers, managing relationships with customers, performing marketing activities and tracking the changes in the market. Hence, an incompetent and low performance sales staff may cause to inefficiencies and failures in these activities and decline in sales. Skills, qualifications and experience of sales people and managers should be evaluated carefully to create a competent and effective sales team.
- **Strategical risk:** The company may decrease the price of the product or even in some situations it may take an order with zero profit. The reasons for such a decision include entering a new market or industry, advertising products, gaining a new customer, or gaining competitive advantage.

iii) Customer related risks: Some of the risks in sales and marketing may originate from customers. Customer payment problems and disruption of customer are two important risk types in this category.

- **Customer payment problems:** Payments delays and defaults may lead to cash flow problems for the company, delays in completion of projects and also negative effects on the whole contractual payment chain. The company does not impose penalties for late payments. However, dealing with slow paying customers and payment defaults take extra time and also create strain on cash flow.
- **Customer disruption:** Customers may be disrupted because of various reasons including bankruptcy, natural disasters, terrorism, labor strike etc. Disruption of the customers results in problems in the completion of the projects and payments of the customers.

Market risk includes the risk factors related with demand, costs, competitors, sector, company's reputation, international business and geopolitical events.

i) Uncertain demand and differences in customers' preferences and needs: The main products of the company are heavy machinery and complete plants. These products/projects have a large volume and weights, and also have a high financial value. The demand for these products/projects is unpredictable and highly volatile. A proactive demand management is vital to cope with the volatility in demand.

Although the company started to a new standardization study for its products (the aim is to assign approximately 90% of manufacturing to producing standard products), currently there is not a standard product. The products/projects are specialized according to the needs and expectations of customers. Volatility in demand and the high inventory holding costs prevents holding stock (or prevents holding a high amount of stock), benefit from quantity discount and standardization of processes, and also lead to capacity utilization problems.

ii) Cost/price risk: Increases in the prices of commodities, energy and fuel constitute a financial treat for the company. Especially iron price (the primary raw material of the company) is highly sensitive to economic and political events. In addition, most of the commodities are purchased in foreign currencies. Hence,

exchange rate fluctuations directly influence commodity prices. Changing prices (e.g. energy price) also affect the accuracy of manufacturing cost accounting and hence profits.

- iii) **Reputation risk:** Reputation risk category includes the factors that damage the reputation, brand image and value of the company. This risk factor may cause to loss of revenue and even bankruptcy. Some of the events that may lead to negative effects on the reputation of the company are as follows: failures in the products of the company, delays in the completion and delivery of projects, health and safety incidents and payment delays of the company.
- iv) **Competitive risk:** Competitors have the potential to threaten the business of the company. Competitor prices, innovations and technological changes developed by competitors and new competitors entering the market may negatively affect the market share and position of the company in the sector.
- v) **International business risk:** The company provides products and services to customers in different countries. International business operations contain various risks inherently. Some of these risks are as follows: political instability, legal risks, embargo, regulatory risk, changes in government policies, fluctuations in exchange rate, tax and tariffs risk, increased customs duty, cultural differences, transportation risk etc.
- vi) **Risks of entering a new market:** The managers of the company make efforts and investments to grow their business. Foreign market entry is one of these efforts. However foreign market entry contains lots of risks and uncertainties including regulatory risk, currency fluctuations, taxes, political uncertainty, difficulties in delivery, cultural differences etc.
- vii) **Exchange rate risk:** It refers to the volatility in a currency. The company operates globally, hence the operations and investments of the company is affected by the changes in currencies. The company uses US dollar as the constant currency in its operations, investments and contracts.
- viii) **Political instability:** It includes political events in the customer's country that cause to cancellation of orders or payment problems; e.g. government change, violence in the society, and coups.

II) Risks associated with product design and development: The company designs machinery and turn-key plants according to the preferences and requirements of the customers. The primary functions of Research and Development (R&D) Department are the development of a new product/plant and updates/modifications/revisions in the existing products according to the customer requirements. R&D department is also responsible for the following functions: product maintenance, warranty, after sales service, quality and regulatory compliance, testing and innovation.

While some orders come with technical plans and drawings, most of the orders require the development and design of the machinery or facility by the focal company. Therefore, the functions of the R&D department have a critical importance for the quality of the end product. Each machinery or plant is treated as a new project and an engineer is assigned as the director and responsible of the project. R&D department also plays an important role in the evaluation of customer orders in terms of manufacturability, production requirements, production costs and time planning. The functions of R&D department is highly related with sales & marketing and production departments. The processes in this department requires a collaborative approach with other departments.

In the light of the information about the functions of R&D department, the risks inherent in this department may be listed as in the following.

- i) Mismatch between customer expectations and project design:** Misunderstanding customer needs, requirements and expectations, inadequate and unclear communication with customers, wrong documentation or transfer of order information (from sales department to R&D department or from R&D to production department) may lead to mismatch between customer expectations and project design. It causes customer dissatisfaction.
- ii) Long design cycle time:** A long design process may cause to delays in projects and loss of competitive advantage.
- iii) Feasibility risk (or manufacturability risk):** Project feasibility studies include the evaluation of the project in terms of different aspects such as time, planning, materials requirement, financial issues, and technical, manufacturing and labor requirements etc. The manufacturability of the ordered projects should be taken into

consideration in the design stage. Mistakes in feasibility studies may cause delays and cancellation of the projects, loss of reliability of customers and loss of money.

- iv) **Uncertainty in new product development:** R&D department performs a detailed research to determine the details of the new product development project. It is a joint study of different departments including sales & marketing, R&D, production and planning. Research phase includes the determination and analysis of product specifications, production requirements, planning, timelines and costs. All of these issues constitute a source of uncertainty.
- v) **Low product and process standardization:** The company produces highly customized products. Low standardization level of both products and processes increase the complexity of the design and manufacturing processes, requires more efforts and time for design and development, and lead to higher prices.
- vi) **Product safety, quality and regulatory compliance risk:** The products must meet the predetermined quality specifications and comply with regulations and standards. Some of the customers request certifications and supporting documentation on product safety, quality and regulatory compliance. Quality related problems and violation of technical and environmental regulatory obligations may cause the following results: damage the reputation of the company, cause legal punishments, lead to financial losses, reduce customer satisfaction, and increase warranty costs.
- vii) **Risks associated with technological change:** Use of outdated technology and low level of technical innovation cause the company to loss its competitiveness and market share.
- viii) **Intellectual property risk:** Protection of the products' design information is very important to sustain the position of the company among its competitors. Loss of intellectual property is protected with design and utility patents, insurance and contracts with partners. Digitalization of product design makes the company more vulnerable to intellectual property risk.
- ix) **Human error:** Human error may lead to poorly designed projects, design failures and mistakes in feasibility studies. It may arise from wrong calculations, bad decisions, lack of experienced engineers and poor control etc. Risks associated with human error may disrupt customer satisfaction, accuracy of feasibility studies, and quality, safety and regulatory compliance of products.

III) Risks associated with the purchasing function (Supply risk): Purchasing department is responsible for supplying the needed raw materials, components, assemblies and services in the right quantity at the right time and from the right sources. The major functions of purchasing department in the company are as follows: i) collection of purchasing requests from other departments, ii) procurement of all of the necessary materials, parts, components, tools and machinery required for manufacturing, iii) procurement of materials needed for daily operations in the office, iv) analysis of the market for the required material or commodity, v) development of a supplier base including potential suppliers, vi) selection and evaluation of suppliers, vii) development and management of relationships with suppliers, viii) inspection of incoming materials, ix) maintaining purchasing, supplier information, supplier evaluation and stock records. This department is also responsible of the planning of delivery services for customers and purchasing of logistics services when needed. The company has a vehicle that is used in the local deliveries. However, for the delivery of high volume products, the company outsource the logistics activities.

The functions of this department are exposed to myriad of risks related with the supply of materials and relationships with suppliers. Especially, the performance of suppliers have a critical importance on the company's success in make to order production systems. Supply related risks that are observed in the company are listed in the following:

- i) Volatility in purchasing prices:** Managing the cost of raw materials, components and assemblies is the top priority of the purchasing department. The company is mainly exposed to the risk of changes in iron and steel prices. Increases in commodity prices may disrupt budget plans, profit and production schedules. Companies have to analyze and track the factors that drive price fluctuations in order to cope with the uncertainty in price and mitigate the related risks. These factors include availability of the commodity, political events, currency fluctuations, increases in energy prices and regulatory changes etc.
- ii) Supplier quality problems:** The quality of raw materials and other components has a critical importance for the company because it affects the quality of the end product. Nonconforming materials and components may disrupt the production process, quality of the end product, sales and reputation of the company. It also

increases warranty and after sales service costs. Incoming raw materials and components are inspected and checked to confirm their compliance to specifications in contracts. The company sends a representative to the facilities of critical parts' suppliers for quality control.

- iii) Supply delivery problems:** Raw materials and other components may be delivered by the focal company, its suppliers or a third party logistics provider. It depends on the agreements with the suppliers and the transportation capability of the company and its suppliers. In all of the situations delays, wrong deliveries, incompliance to shipping instructions, packaging quality problems may disrupt production schedules. Working with international suppliers brings additional risks related with the political events, shutdown of ports, excessive handling due to border crossings etc. Geographical location of suppliers, weather and climatic conditions, transportation route failures, poor packaging, driver errors, vehicle related risks and traffic are some of the factors that cause to supply delivery problems (Wu and Olson, 2008; Chan and Kumar, 2007). Transportation responsibility, shipment instructions, packaging details and transportation costs should be evaluated in determining supply costs and clearly specified in the contracts with suppliers.
- iv) Inadequate supplier management:** Suppliers have a critical importance for the success of make to order manufacturing systems. Selection and evaluation of suppliers, development of supplier management programs and management of supplier relationships directly affect operational performance, quality of the products, production schedules and company's reputation. This risk category includes inadequate supplier selection methods, lack of supplier development problems, inadequacies and failures in evaluating suppliers, lack of standards in measuring and monitoring performance of the suppliers, and weak or ineffective control of suppliers etc.
- v) Procurement and contract management failures:** There may be mistakes and shortcomings in procurement transactions, contents of contracts and their tracking. It may result from wrong data entry, wrong calculations or oversight of the purchasing staff.
- vi) Contractual risks:** The contracts should cover the descriptions and specifications of the incoming supplies, description of the requested quality level, price and terms

of payment, logistics charges, required delivery date and, shipping and packaging instructions. A missing issue may pose a problem between the company and its supplier.

vii) Poor supply planning: This category includes the risks related with the problems and ineffectiveness in planning and managing the supply of raw materials and other components required to fulfill an order. Inaccuracy in the identification of the amount of required supplies, planning of the delivery dates, specification of the desired quality level and calculation of the budget disrupts manufacturing processes and customer satisfaction.

viii) The risk of dependency on suppliers: Manufacturers are dependent on their suppliers, but the level of the dependency is very important. Too much dependence on suppliers, high degree of outsourcing, dependency of critical functions on suppliers, lack of sourcing flexibility, single sourcing, lack of alternative suppliers and inadequacy of capacity and responsiveness of alternative suppliers constitute a risk for the company. As mentioned in Section 6.2, the company has a subsidiary casting company. The casting factory operates individually and it is one of the suppliers of the case study company. However, the relationship between the companies decrease the supply risk related with the products that are supplied from this supplier (especially supplier dependency risk).

ix) Disruption of the supplier: Suppliers may be disrupted because of different reasons including natural disasters, fire, bankruptcy, insolvency etc. (Nekooie et al., 2015). Although this risk category has a low frequency, it may lead to severe consequences. The company should track the factors that threat the continuity of supply. Vulnerability of the suppliers to natural hazards and accidents, condition of machines and production equipment, and financial instability of the supplier are some of the trigger factors of supplier disruption risk. Failures in sub-tier supply networks may also disrupt suppliers; hence, the supplier management studies of the suppliers should be regarded in supplier selection.

x) Shortage of raw materials: Sometimes suppliers choose to hold their products due to news about a price increase (especially metal suppliers). Production is affected from shortages of raw materials very much.

- xi) Lack of supplier flexibility:** Supplier flexibility is the ability of the supplier to respond to changes in the buyer's demands in terms of product, volume and delivery dates (due to capacity limits). Lack of supplier flexibility increases the response time to customers' requests about changes in demand and product design, and decreases the competitive advantage of the company.
- xii) Relational risks:** This category includes the risks related with the relationships between the company and its suppliers. The followings risks may be listed within this category; bargaining power of suppliers, reliability problems, lack of trust, disloyalty, cultural differences, collaboration risk, decline in business relations with suppliers (e.g. breach or canceled contracts).
- xiii) Poor communication and coordination with suppliers:** Communication and coordination with suppliers is a key success factor for SCs. The factors that lead to poor communication and coordination with suppliers may be listed as follows: unstable and inefficient communication networks, information flow disruptions, lack of transparency, misinterpretation of the emails by suppliers, problems with the availability and continuity of contact persons, unwillingness to share information, and lack of supplier audits (Kull and Talluri, 2008; Ruhrmann et al., 2014; Guertler and Spinler, 2015). Failures in communication and coordination with suppliers may result in wrong incoming supplies, quality problems, delivery failures, bad relationships with suppliers etc.
- xiv) International business risks:** Although working with international suppliers exposes the company to a higher number of risks than working with domestic suppliers, the company sometimes prefers to work with a foreign supplier in order to gain lower supply costs. Some of the risks related with working with a foreign supplier are as follows: exchange rate risk, tax and tariffs, duty factor, import restrictions, complexity in shipping procedures, border crossings, political risks, country risk, language differences, cultural differences etc.
- xv) Poor service capability and irresponsiveness of the supplier:** After sales service provision, quick response and problem solving capability of suppliers are important to handle with a supply related problem.
- IV) Risks associated with the production function:** Production planning department is responsible for the planning and control of the production processes. The main

functions of the production planning and control department are listed in the following;

i) Identification of the requirements for materials and other commodities, labor force, and types of machinery and equipment to fulfill an order, ii) Development of the production schedule for each order that includes the time table for the use of resources, machinery and processes, iii) Identification of daily production targets, iv) Identification of the tasks and their timetable, v) Allocation of the tasks to workers, vi) Controlling whether the production progresses according to the production plan, vii) Improvement of the efficiency of the manufacturing and assembly processes, viii) Maintenance of machine and equipment that are used production and ix) Identification of the production costs.

Most of these functions are performed with a collaborative study and discussions with the production department. Production is highly dependent to the purchasing department for the supply of required materials and other components in the manufacturing processes. These two departments work in collaboration to mitigate the effects of risks related with the supply function. Production department also works closely with the design department in order to ensure that the products are in the desired quality level and conform to the specifications of the customers.

Production planning process is exposed to various risks. These risks are explained in the following.

- i) **Capacity risk:** Capacity planning and management is very important for the company due to the variability in demand. Capacity related problems include uncertainty in production capacity, low capacity utilization, incompatibility between demand and the capacity of the company, capacity shortages, excess capacity and warehouse capacity limitation (due to the high volume products/projects). These risks result in missed orders, underutilization of resources (raw materials, labor, machinery and equipment etc.) or low operating efficiency. The company has a make to order strategy and its capacity varies due to the type of product. Hence measurement of capacity is very critical to assess and monitor the efficiency of manufacturing and capacity risk.
- ii) **Inadequate manufacturing capability and flexibility:** The company develops and produces highly customized products and projects. Hence, it is very important to

have a high level of manufacturing capability and flexibility to respond to changing customer demands and production levels. This risk category includes technical and physical limitations of manufacturing processes, material handling, machine, equipment, warehouse and labor force. These risks may cause the company to lose its competitive position and customers.

iii) Operational/process risks: It includes the risks that lead to poor operational performance.

- **Process management related risks:** This risk category includes faulty design of operations, inefficient process planning, wrong procedures and incorrect operation sequence. These risks affect the efficiency of the manufacturing system and the quality of the end product. Due to the make to order strategy of the company, product/project designs change according to the needs of the customers. Product design influences process design, hence process design and management is an important issue for the company.
- **Poor operational performance:** It refers to the deviations from a target operational performance measure such as execution time of a process, lead-time, cycle time, production rate, process stability, quality, productivity, etc. Low operational performance may result from a myriad of factors including poor quality raw material, long setup time, variations in customer demands, poor communication and coordination between different departments (e.g. sales and R&D) or between management and employee, poor employee performance, human error and poor planning capability of the staff etc.
- **Quality problems:** Quality inspection department is responsible for quality control and inspection for the incoming materials and components, and ensuring the quality of the end products. Quality problems are non-conforming materials and supplies, rejected items, high rate of rework/reprocess needed, poor quality products (design, performance, and efficiency) and quality complaints etc. These problems bring additional costs including costs of reprocessing, warranty and after sales services. Quality problems can cause to poor quality products, low customer satisfaction, decrease in sales, and damage to the reputation of the company and brand image etc. In addition to incoming commodity inspection, the company applies quality control process at the end of each manufacturing

process and at the final step. In addition, quality related problems are recorded by the quality assurance team. Root causes of quality problems should be analyzed carefully to mitigate quality risk. Quality related issues may result from problems related with materials, people, processes, machinery or equipment.

- **Breakdown of equipment and machinery:** Machinery and equipment breakdown is an important risk that threatens the whole production system. A breakdown of the equipment or machinery may result from improper and inadequate maintenance, inaccurate calibration, corrosions of components, operator error, delicate or failure prone equipment or improper material. These problems always cost extra time and money for the company. A delay in a workstation may affect the whole production system and cause delays in customer orders.
- iv) **Occupational accidents:** Accidents pose a big threat for human health and life. Operational accidents can cause serious injuries and even loss of human life. The frequency of accidents is very low, but it may cause too severe consequences. The following precautions should be taken in order to prevent undesirable incidents; i) Facility layout, machinery and equipment should be designed by considering safety characteristics. ii) The employee should always wear the required uniform. Occupational accidents are reported to the associated government authority, iii) Posting safety guidelines around the workplace.
- v) **Poor working conditions:** Poor and unsatisfactory working condition includes the risks arising from long working hours, poor wages, poor physical work environment (e.g. unsafe and unhealthy working conditions, high noise levels, high/low temperature, lighting, unmet hygiene factors), work related stress and poor work design, organization and management etc. Poor working conditions increase the risk of low quality products, employee dissatisfaction employee turnover, occupational diseases, and occupational accidents. The job of the company has a dangerous and difficult structure. Hence, occupational health and safety risk has a critical importance. The company is legally responsible for providing a good, healthy and safe working environment. The employees in the company use protective clothing and equipment in the work area.

vi) Inadequate performance measurement and management systems: The company does not have an effective performance management system. There are not sufficient performance measures and auditing processes to track the productivity and efficiency of the processes, machines and labor. They only record the actual time of each process. These issues prevent identification of the areas that are faulty or need improvement.

vii) Poor manufacturing planning and scheduling: Accuracy and efficiency of production plans and schedules have a huge impact on the overall production cost and efficiency. The most important problem that decreases the performance of the planning procedure is the lack of an ERP system. Another problem related with poor manufacturing planning is that sometimes the employees give faulty information about the processes (e.g. longer processing time).

V) Risks in transportation and logistics: Transportation and logistics activities are performed according to the international transportation and logistics standards that is specified in the sales contracts (Incoterms). Sometimes the customers bear the responsibility for the whole transportation process or a part of it. As an example, foreign customers may prefer to take their orders from ports. However generally the current company outsource the logistics function from a third party logistics provider. In addition, for small sized orders the company uses its own trucks locally. In both situations transportation and logistics risks threat the business of the company. Transportation and logistics risks may be listed as in the following:

i) Delays: Failure to transport on time damages customer satisfaction and brings penalty fee depending on the contracts. Delays may be caused by the following factors; long distances, bad weather and climatic conditions, driver related issues, accidents, transportation route failures (e.g. port stoppage and piracy), vehicle related problems and traffic etc.

ii) Incompliance to shipping instructions: Shipping details are included in the sales contracts. Incompliance to predetermined shipping instructions cause loss of customer satisfaction and even can cause damages to the product. Inappropriate shipping conditions include incompliance to transportation standards, improper loading etc.

iii) Poor packaging: Low quality packaging can cause damages to the products.

Working with international customers brings additional risks related with the political events, shutdown of ports, excessive handling due to border crossings etc.

VI) Risks associated with the management function: Management function contains various components and operations. Management has a broad range of responsibilities. Managers are responsible for financial management, planning, organization of business, coordination, evaluation of performance reports, controlling, approval of decisions, staffing and regulatory compliance. The risks associated with the decisions of the company manager are listed in the following:

- i) Poor and ineffective management:** This risk category includes poor business decisions, inefficient or faulty planning and coordinating procedures, poor SC design and coordination, poor financial management and inadequate performance management system. It may lead to low productivity, inadequate resource allocation, decrease in profits and poor relationship between management and employee. The company has a highly qualified and experienced management. However, the contents of the reports that are used to evaluate different decisions are not sufficient. The decisions of the company mostly depend on subjective evaluations. Hence, it is needed to identify and use different metrics in order to make objective and effective decisions. Data analysis will enhance the effectiveness of the management function.
- ii) Strategic risks:** This risk category contains the risks related with business strategy decisions such as launching a new product, entering a new foreign market, determining the degree of outsourcing etc. Strategic risks include faulty and inappropriate strategic decisions, bad investments and wrong budgeting etc. Strategic risks impact the achievement of the company's goals. These risks can arise because of insufficient provision of management and wrong calculation of organizational metrics that are used in the evaluation of managerial decisions.
- iii) Risks related with the security of physical assets:** Security and safety of physical assets of the company is an important problem that treats the company. A theft occurred in the old plant in the company. After moving inside organized industrial site, the probability of the security and safety risk has declined. However, the

company should take precautions to protect the security of business assets such as physical access restrictions and monitoring systems.

iv) Regulatory risk: Instability in government policy and regulations, some of the changes in regulations or laws (e.g. changes in fees, uncertainty in export/import costs and restrictions), regulatory compliance problems and stringent government regulations negatively affect the business. Government regulations such as legislations relevant to different issues (e.g. environmental obligation, workplace health and safety, working hours and wage etc.) may bring extra costs and workforce. Regulatory risk differs according to the industry. Related legal and regulatory initiatives should be monitored carefully by the company. Incompliance to environmental standards and regulations may lead to financial losses, penalties, and loss of reputation and customers.

v) Financial risks: It includes the risks related with financial operations and transactions of the company. Some of these risks are; economic uncertainty, weak economic climates, economic crisis, volatility in commodity prices, increases in energy prices, currency fluctuations, interest rate risk, tax risk, increasing customs duty, cash flow risk, bearing and funding risk, credit risk and delayed payments etc. Changing prices (e.g. energy price) also affect the accuracy of manufacturing cost accounting.

One of the most important financial risks for the company is customer payment default risk. The company generally extend the payment due date of customer when they fail to pay. Although the company accepts this risk due to not damage the relationship with customers, it may lead to severe cash flow problems in the long term.

vi) Inadequate corporate environmental and social responsibility: This risk may decrease the sales and damage the reputation of the company in the market. The company performs the following activities for their corporate social responsibility: collaborative studies with universities, sponsorship and scholarship programs. The social responsibility process may be improved by assigning a responsible person and developing a procedure for this area. In terms of environmental responsibility of the company, there are some environmental regulations and standards for waste management and environmental pollution. Violation of these standards leads to

punishments. The company may also implement an environment friendly approach to enhance its reputation in the society. Inadequacy of both corporate environmental and social responsibility can have a negative effect on the reputation of the company in the market and society, and cause loss of customers.

vii) Poor organizational structure and design: Organizational structure of a company includes organization of the functions, responsible people, job details and hierarchy. There are some problems related with the organizational structure and design in the company; i) The functions and responsibilities are not defined properly and clearly. ii) There is a considerable role confusion, inconsistency and complexity about the role, authority, job description and responsibility of the staff. iii) The organization chart and procedural guidelines are outdated. The company has a growing trend; hence, these documents should be reviewed and updated with the changes and developments in the company. Poor organizational structure decreases the efficiency of business processes, productivity and the profitability of the company.

VII) Risks associated with financial and accounting functions: Accounting department is responsible to keep the records of financial transactions. Financial and accounting activities are one of the most important functions in every organization. Financial transactions are dependent on the confirmation of management. Therefore, financial risks are covered in the management part. Financial risks include the factors that threaten the financial position of the company such as decreases in revenue and profit, cash flow problems of the company, volatility of commodity prices, changes in interest rates, and volatility of exchange rate (FDIC, 2015).

Information and audits provided by the accounting department is very critical for the accuracy and effectiveness of financial decisions and the evaluation of the current position of the company. However, there is not a systematic and detailed reporting procedure (inadequate financial records, performance metrics and statistical analysis etc.) for the financial activities of the company. This creates a big risk that leads to wrong and inadequate assessment of the company's financial status, assets and performance level.

VIII) Risks associated with human resource management: The major functions of the human resources department are as follows: i) recruitment, selection and retention of employee, ii) planning of orientation programs, iii) identification and planning of training programs to develop the skills of workers, iv) ensuring compliance with labor and employment laws, and prevent wage and hour lawsuits, v) evaluating employee performance, vi) maintaining a good, healthy, safe and comfortable working environment, vii) ensuring employee welfare and motivation, viii) management of employee relations. Human resources department is exposed to the risks related with labor issues. Labor related risks that are identified with the discussions, brainstorming and a focus group study with the company are listed in the following.

- i) Low employee satisfaction and demotivation:** The lack of employee satisfaction and motivation cause poor performance levels, decrease the productivity of the company and increase employee turnover rates. The factors that lead to employee dissatisfaction should be analyzed to mitigate this type of risk. Lack of employee satisfaction and motivation may result from various reasons including inadequate or unfair salaries, work stress, mismatch between employee and job, poor working conditions, poor management-employee relations, tense labor relationship and job conflict. The company performs a survey study to measure employee satisfaction each year. There is also a wish and complaint box that is used to identify the problems that disturb the employee.
- ii) Poor working conditions:** The job of the company is very hard and tiring. Also the workplace environment does not have a comfortable and safe structure by its nature. These factors increase the risk of poor working condition. Some other risk factors within this category are unbearable working conditions, excessive working time, insufficient breaks, negative health effects, high noise levels, improper workplace temperature, use of outdated and improperly maintained equipment, machines, etc. Poor working conditions may cause to customer dissatisfaction, occupational accidents, and legal penalties.
- iii) Noncompliance with labor and employment laws:** It includes the risks of incompliance with laws and regulations associated with working hours, wages, overtime pay, firing process, workers' compensation and workplace safety & health standards. Noncompliance with laws can cause employee complaints, unsafe

working conditions, legal fees and penalties, lawsuits and prison sentence. Human resources specialist should track the changes in laws and regulations associated with employee.

- iv) Poor work performance:** This risk category includes poor or unsatisfactory performance, employee's carelessness, violation of rules and negative behavior that impact other personnel. Poor employee performance may lead to low productivity, decrease in revenue and unrest in working environment. The most common causes of low performance levels are lack of needed talent and qualifications, lack of experience, insufficient/improper training, work related stress, employees' personal problems, poor employee satisfaction and absenteeism, etc.

In addition, the company does not have a performance management system. It causes the lack of subjective measurements of employee performance.

- v) Loss of a key staff member:** A key employee may quit because of job dissatisfaction, career move, illness, disability or death. It can damage the processes in the company and cause expenses due to replacement of the person (including reduced productivity, recruitment and training costs etc.). The company should listen its labor and pay attention to the results of employee satisfaction surveys. Job descriptions and process flow charts are not sufficient and clear. This situation increases negative effects of losing a key staff member.

- vi) Unavailability of qualified labor:** Difficulty in finding and recruiting qualified labor is an important problem for the heavy machine industry. It is very hard to find an employee with a good level of knowledge, experience, training and skills relevant to the job of the company.

The employee turnover rate is not very high. Most of the labor in the company has been working for a long time in the company. Hence, although the impact of this risk is very high, it has a low frequency.

- vii) Infectious diseases:** The most common infectious disease in the work place is flu. Flue pandemic causes absenteeism of labor and has a high negative effect on labor performance.

IX) Risks associated with the Information System: The company outsources its information technology systems (infrastructure support etc.) to a service provider firm. Information technology is a vital part of the business. Information technologies enable

the storage and maintenance of company data on servers and the access of the employee to the data when needed. Data is very important for the company. Information system helps to collect, process and interpret data according to the needs of the user and support decision-making processes. Companies track their sales, processes, productivity, performance, profitability and risks with the information gathered by the analysis of the data. A failure or disruption in information technology may lead to the following results: inefficiency or failures in business operations, financial losses, loss of customers, loss of stakeholders' trust, and ineffective and insufficient communication. The risks related with information technology infrastructure and information system are listed in the following.

- i) **Ineffective information system:** The company uses Microsoft Excel to collect and manage its data. Some of the problems related with the current information system are as follows: i) This system is very vulnerable to human error. ii) The types of collected data is not organized properly and also insufficient. There is lack of performance measurement studies. iii) The excel files of departments are separate from each other and there is not an integrated information system structure (data integrity problem). iv) Excel is not used efficiently.
- ii) **Information system failure:** If the information system does not operate for a specific time period or does not perform as planned, the company faces serious consequences including disruption of operations, interruption of production, loss of revenue and loss of customers. Information system may fail because of various factors such as poor information technology infrastructure, user failures, cyber-attacks, deliberate acts etc.
- iii) **Failures or disruptions of information technology infrastructure:** A failure or inadequacy of information technology infrastructure disrupt the business of the company. It may result from poor technological infrastructure, malfunction of an infrastructure component, faulty hardware, human error, inadequate hardware maintenance, internet outage, deliberate acts or natural disasters (Mouatassim and Ibenrissoul, 2015).
- iv) **Risks related with the security of the information system:** This risk category includes the threats related with insufficient security policies, authorization error or unauthorized access, data access, user accounts, data backups, firewalls vulnerable

to attacks, hackers, malwares and viruses, and fraud by employees. The information system service provider is responsible for the security of the system. In addition, it is forbidden to use usb memory in the company because of security countermeasure.

- v) **Software integrity problems:** The company is negotiating with different software vendors in order to develop a new information technology system for the company. This will lead to integrity threats while adapting the new system such as mismatch between the system and the organization, improper reporting etc.

X) Other Risks: There are some other unforeseen events that threat the organization and the SC. Although these risks are rare, they can cause to severe disruptions. These risks are given in the following.

- i) **Catastrophic risks:** The losses resulting from catastrophic events have been increasing in the world. Hence, companies pay increasing attention to this issue. Therefore, catastrophic risks that have a low frequency and high impact are discussed separately. Some of the catastrophic risks are; i) natural disasters: e.g. earthquake, hurricane, tornado, volcanic eruption, floods, tsunami, typhoons, storm and landslide, ii) extreme weather and climatic conditions: e.g. heavy rain, extreme heat, blizzards, lightning and climate variability, iii) epidemic, iv) terrorism, v) war, vi) accidents (Er Kara Oktay Firat, 2015). All of these events have serious disruptive affects such as building collapse, human death and bankruptcy. The company should evaluate the location of the factory in terms of the mentioned risks and develop emergency plans.
- ii) **Deliberate threats:** There may be deliberate actions or incidents that threat the company such as theft, sabotage, industrial spying, frauds and patent infringements, and terrorism.

There are various sources of risks for companies. Some of the risk factors are eliminated after evaluating their frequency and possible impacts on the company and its SC.

6.4. Identification of Risk Indicators

The first step in developing the RDW is to determine and clearly define the risk related indicators/metrics. Risk indicators are used in risk identification, measurement,

assessment and monitoring of risks and detection of the changes in risks and emergence of new risks (Scarlat et al., 2012). Risk indicators help to determine where to focus our risk management efforts. Identification of risk indicators is a critical part of the DM-based SCRM model. This step has a critical importance for the success of the proposed DM based risk management model. For detailed information about risk indicators, we refer to Section 4.3.

There are thousands of risk indicators that are used in the academic studies and business life (Scarlat et al., 2012; Stillwagon, 2015; Buttle and Maklan, 2015). They give information about the level of risks. The risk indicators that are proposed in this study are determined specifically for the current company. Risk indicators that may be used in measuring, assessing and monitoring the selected risks in the company are determined with a collaborative study with different departments and management. A top-down approach is used while determining risk indicators (Mouatassim and Ibenrissoul, 2015). The determined risks are evaluated by considering their criticality and measurability and the number of risks are reduced to a manageable level. The key risk indicators are determined with the management and then evaluated with the operational staff within different departments. The sector, business structure and objectives, risk attitude, and need of the company are considered while determining these risks. Some of the risk indicators are eliminated after evaluating the necessity to collect and analyze them (Parmenter, 2012). The final set of risk indicators are developed with discussions and a focus group study. While a few of these indicators are currently measured and collected by the company, most of them are new indicators that are proposed to the company to create an effective risk management structure.

The selected set of risk indicators include the four types of risk indicators proposed by Chapelle (2013): exposure, stress, causal and failure indicators / failed KPIs (See Section 4.3). They can be used to measure and track the company's exposure to the pre-determined critical risk factors. The determined risk indicators that are associated with each risk type are introduced in the following.

1) Indicators of customer dissatisfaction: Customer feedbacks gained from customer complaints and customer satisfaction surveys may be used to measure and assess customer dissatisfaction risk (Trayes, 1997; GAO, 2000).

Customer complaints: Customer complaints should be assessed and managed carefully. Customer complaints should be stored in the database to measure frequencies and trends of different issues in customer complaints. Customer complaints may include problems related with products, services, processes or employee etc. The following risk indicators may be obtained from customer complaints data (Landon, 1980; Marr, 2012):

- **Total number of customer complaints:** It refers to the total number of complaints received in a time period (Matruglio and Tymmons, 2014; Lynch, 2015; Davies et al., 2006). An increase in the number of complaints can help to early detect a problem.
- **Percentage of customer complaints by reason:** It is calculated by dividing the total number of customer complaints associated a certain issue by the total number of complaints in the same period. This indicator is important to assess the sources of customer complaints and identify the problematic areas.
- **Complaint escalation rate:** It represents the number of customer complaints that cannot be solved by the customer service staff and escalated to higher levels (managers) by the customer (Stillwagon, 2015). It is very important indicator of losing a customer. Instead of escalation rate, the company may also use complaint escalation rate by reason and number of complaint escalations per sales representative or technical support staff.

Customer satisfaction surveys: The dissatisfaction level of customers on different facts may be measured by applying customer satisfaction surveys (GAO, 2000). These surveys include ratings of customers on their satisfaction about different aspects of experience including quality of the product/ service, design of the product, technical service, representative's availability, delivery performance, complaint resolution etc. The facts that cause customer dissatisfaction and need to be improved may be identified by using the results of the surveys. Also decreases in satisfaction levels may be captured by this data. In addition, customers may be grouped according to their dissatisfaction levels.

The following risk indicators may be obtained by asking different questions to measure customer dissatisfaction and disloyalty (Landon, 1980; GAO, 2000; Stillwagon, 2015; Buttle and Maklan, 2015):

- **Percentage of dissatisfied customers:** This is the most basic and common indicator that shows the dissatisfaction level of customers. Ratio of dissatisfied customers is calculated by dividing the number of dissatisfied customers by the total number of customers replied to the survey in a specific time interval.
- **Customer dissatisfaction ratings:** Customer surveys should include questions about the satisfaction levels of customers on different issues/attributes/services (including attitude of the sales representatives, after sales services, communication, reliability etc.). These ratings help the company to identify root causes of customer dissatisfaction, and distinguish and compare customers' dissatisfaction levels according to different issues/services or customer type (Trayes, 1997).
- Customer surveys and complaints are important to gather customer dissatisfaction and market risk related data (GAO, 2000). These documents give information about the dissatisfaction levels of different types of customers about different aspects and changes in dissatisfaction levels. In his bachelor's thesis, Stoop (2009) developed a reference model for key performance indicators and dashboard reporting for sales and marketing.
- **Overall dissatisfaction score of customers on a product or service:** Overall dissatisfaction level measures the general dissatisfaction level of a customer (Matruglio and Tymmons, 2014; Stillwagon, 2015; Buttle and Maklan, 2015). It is also an indicator of the likelihood of a customer not to repurchase and recommend the brand to someone.
- **Total number/percentage of customers that do not want to repeat business with the company:** It represents the total number/percentage of customers in a time period that do not think to repeat business. It is a measure of business loss and customers' disloyalty.
- **Net promoter score:** It measures the likelihood of a customer to recommend the brand to someone (Stillwagon, 2015). Dissatisfied customers do not recommend the brand to others. Hence, it is another indicator that may help to measure customer disloyalty.

The sales department interacts with customers hence data and information on customer related risks may be obtained and collected by this department. Sales department receives customer complaints and also apply a customer survey to their customers.

2) Indicators of poor sales performance: The following indicators may be used to measure and track inefficiencies and performance problems related with the sales process and the sales staff:

- **Revenue:** Revenue is the income generated from business (sales of products or services) in a specific time period (Stoop, 2009). A decrease in sales revenue may be a sign of poor sales performance, loss of customers and lack of growth (Matruglio and Tymmons, 2014). Sales growth rate can also be used instead of sales revenue. It measures the percentage of increase in sales between a given time period.
- **Gross profit margin:** It is the ratio of the difference between revenue and cost of goods sold to the revenue (Marr, 2015). It can be used to detect a decline in profitability and sales.
- **Net profit margin:** It is the ratio of net profits (revenue left after all expenses have been subtracted) to the company's total revenue (Lynch, 2015; Dietrich, 2016). It should be evaluated with gross profit margin to identify risks.
- **Customer churn rate:** It is calculated by dividing the total number of customers lost (that do not repeat business) over a given time period divided by the total number of customers in the same period (Buttle and Maklan, 2015). It is a measure of business loss and customers' disloyalty. It may be evaluated together with the results of customer dissatisfaction surveys.
- **New customer acquisition rate:** This indicator refers to the total number of new customers that are acquired in a given time period (Matruglio and Tymmons, 2014; Buttle and Maklan, 2015; Opsdog, 2017).
- **Conversion rate:** It represents the likelihood of making business with the customers that are interacted by the sales team (Stillwagon, 2015; Lynch, 2015). The reasons of not converting the potential customers to real customers give information about the areas that need to be improved. A low conversion rate may result from poor performance of the sales representative.
- **Percentage of repeat customers:** It is the number of customers that have completed multiple purchases divided by the total number of customers in the given time period.

- **Failure rate of orders:** This indicator refers to the percentage of wrong customer orders such as orders delivered with wrong documentation (e.g. invoice) or incompliance to packaging and shipping standards etc. (Opsdog, 2017). The reasons of the failures in orders should also be documented in order to evaluate the sources of these failures.
- **Customer dissatisfaction indicators:** Customer satisfaction is positively correlated with sales performance (Landon, 1980). Hence, customer dissatisfaction indicators may also be used to measure sales performance of the company.

The performance of sales team has a huge impact on the sales performance of the company. A poor performance of a staff member may cause to both customer dissatisfaction and low sales performance risks. Hence, performance indicators about sales staff should be measured and tracked to detect a decrease in their performance or inadequacy of the employee. The following risk indicators may be used to measure the risk of poor performance of sales representatives (Teau and Protopopescu, 2015; Opsdog, 2017):

- Average number and value of sales per sales representative
- Average revenue per sales representative
- Sales win rate per sales representative
- Average sale turnover per sales staff
- Average sales cycle length per sales representatives / Time spent selling per sales representative (Duration of each sales stage may also be stored to detect the steps that need improvement)
- Percentage of Human-Related Order Errors

3) Customer risk indicators: Customers should be evaluated according to their risk profile. The following indicators are selected for the measurement and evaluation of customer risk. Customers should be evaluated based various points of view. The following subjective evaluations and quantitative metrics can be used to calculate a risk score for customers: geographical location of the supplier (distance, type of transportation modes etc.), past business data, customer payment data, currency rate that the customer pays, and customers' financial status (Trayes, 1997).

4) Market risk indicators: This category includes the risk indicators that are determined to measure and track the market risks related with increasing prices, reputation of the company and position of the company in the sector. Related data may be gathered from market research reports, consultancy firms or market surveys (Marr, 2012).

- **Commodity price indices:** The increases in commodity prices (raw material, parts etc.) increase manufacturing costs. Commodity price index (e.g. raw material price index) measures the change in commodity prices purchased by the company. It may alert the company to make strategic decisions to cope with the volatility in commodity prices.
- **Product market share:** It refers to the market share of company's products compared with its competitors (Matruglio and Tymmons, 2014; Teau and Protopopescu, 2015). The company should track its market share in order to detect a decline its competitive position. A decreasing market share may also result from a new competitor that has entered the market.
- **Market growth rate:** Market growth rate is calculated by dividing market size in a specific time period to the market size of a previous period (Stoop, 2009; Marr, 2012). Market size may be measured by the total value (or total number) of sales in the market. A decline in the size of the market may be a sign of the problems in the sectors that the company serves, a growing financial crisis, harder regulations in the sector, or emergence of a new product or technology.
- **Exchange rate:** It is the price of one country's currency in terms of another country's currency. The international business structure of the company makes exchange rate one of the most important risk factors for the company (FDIC, 2015).
- **Website statistics:** The number of people visiting the website of the company and pages viewed may provide insights about the success of the marketing activities.

5) Indicators of poor quality customer service: The following indicators may be used to measure and track customer service related risks.

- **Customer service dissatisfaction rate:** The data on this indicator may be obtained from customer dissatisfaction surveys and complaints. Both the number/percentage of dissatisfied customers about customer service and the ratings on the customer services may be used as an indicator of poor quality customer service.
- **Response time to customers' service requests:** The company makes a promise to respond to service requests within 24 hours. Therefore the response time to customer requests should be recorded and tracked. Response time is the time elapsed between receiving the customer request and the response of the company to this service request (Lynch, 2015; Parmenter, 2012). Response time can be used in the identification of weaknesses in service levels and customer dissatisfaction on service. This indicator may also be calculated per project manager/technical staff that are responsible for after sale services.
- **Percentage of delayed services:** This indicator can be calculated from the response time data. Similar to response time, it is an indicator of low service level and customer dissatisfaction (Matruglio and Tymmons, 2014).
- **Resolution time:** It is the total time (in hour per person) that is spent to resolve customer requests, complaints and problems (Trayes, 1997; Parmenter, 2012; Stillwagon, 2015). Malfunction of the projects of the company can cause huge financial losses for customers. Hence the company should repair machinery or system as quickly as possible. Therefore this indicators is very critical for the company and can be used to detect low level customer service, poor performance of technical staff and customer dissatisfaction risks.

6) Quality risk indicators: The following indicators can be used to track and monitor the risks associated with the quality of projects, end products, raw materials and parts.

Indicators that are used to measure in-process quality risks:

- **Total number of defects observed in manufacturing processes:** The company performs a quality inspection process after each manufacturing process in order to check the quality of the processed items. All of the quality problems are recorded in detail by the quality insurance department. Internal quality audit reports include the explanation of the quality problem, its reason, and corrective actions (Dietrich, 2016). Total number of manufacturing defects

observed in a specific time interval can be used to track the quality level in manufacturing (Parmenter, 2007). The number of defects per causes can also be used in order to gain additional insights about the sources of quality risk (e.g. a defect may result from bad materials, human error or equipment failure etc.) (La Londe, 2016).

- **Cost of quality correction as a percentage of sales revenue:** This metric is calculated by dividing the total costs of quality correction to the total sales of revenue in a specific time interval. Cost of quality correction refers to the costs of scrap, rectification and rework (Parmenter, 2007; Marr, 2012; La Londe, 2016; Dietrich, 2016). It represents problems in the quality of manufacturing processes.
- **Total time spent on quality improvement activities:** In addition to cost of quality correction, total time spent on quality improvement activities is an important indicator of in-process quality risks (Parmenter, 2007).

Indicators that are used to measure the quality risks in end-products/projects:

- **Warranty costs as a percentage of sales revenue:** This indicator measures the rate of the warranty expenses including cost of technical assistance, repairs, labor and changes of machinery parts or components to total sales revenue in a given period (Blischke and Murthy, 1994; La Londe, 2016). An increasing number of warranty claims and cost imply that the product quality is decreasing (Dietrich, 2016). The company records the warranty claim, its reason, performed repair activities and cost.
- **Total expenses for technical support (customer service) per project:** This indicator refers to the total volume of expenses that is spent for the technical support of a project. Each project has a project manager who is a product design engineer. Technical support expense may also be used as an indicator of low performance and inadequate control of the project manager.
- **Number of breakdowns within 90 days of operation:** Number of mechanical breakdowns and failures in the delivered projects within a specific time period can be used to measure and track quality level of products (Parmenter, 2007). The length of the time interval should be determined by the design department and it may vary according to the type and complexity of the project. The

reasons of the breakdowns should also be recorded for the identification of the common causes of breakdowns.

7) Indicators of poor design process: Customer surveys and complaints provide information about the dissatisfaction level of customers about the design, quality and performance of the projects/products they have bought. There are some other indicators that provide insights about the performance of the design team.

- **Project design cycle time:** It is the number of days spent to design a new project/product (Parmenter, 2007). Each order is designed and developed according to the needs of the customer. Hence only the time spent to complete the details and drawings of the project is incorporated in this indicator. This indicator can be used in the identification of the design staff members with poor performance levels or the product types that requires longer design cycle time.
- **Number of revisions after the completion of the design:** It refers to the number of engineering changes after the completion of the project design (Parmenter, 2007). Frequent design changes may be a sign of the following risks: i) poor performance design processes and staff, ii) wrong, incomplete or inadequate information flow from customers, iii) poor communication with suppliers, and iv) poor communication between departments.

8) Supply risk indicators: There are various risk factors associated with the supply of raw materials and other components (Er Kara and Oktay Firat, 2015; Guertler and Spinler 2015). The following risk indicators can be used to measure, assess and monitor supply risks.

- **Supplier evaluation surveys:** Supplier performance evaluations give information about the risk levels of suppliers (Scandizzo, 2005). The sales staff gives ratings to customer on different issues including quality, delivery performance and x. These ratings are used to calculate an overall performance value for the suppliers of the company. However the supplier evaluation criteria are not adequate. New evaluation criteria should be used for supplier evaluation and selection process. The following criteria may be used in evaluating suppliers (Guertler and Spinler, 2015; HPWQLD, 2014); compliance to specifications, parts quality, packaging quality, compliance to shipping instructions, product

costs, logistic costs, financial stability of the supplier, supply market exchange rate, hedging transactions, willingness and openness for information sharing, availability and continuity of contact persons, precise and quick communication, effectiveness of sales support, service quality, technology and product know-how, volume flexibility, minimum batch size, condition of machines and production equipment, and percentage of supplier's work commonly subcontracted etc.

- **Surveys applied to suppliers:** The company may gain additional information about suppliers' risk profile by applying questionnaire to them. These surveys can include questions about the company size, industry knowledge (experience), presence of quality and risk management certifications, and percentage of supplier's work commonly subcontracted etc. (Kannan and Tan, 2002).
- **Number of late and inaccurate deliveries by a supplier:** This indicator refers to the number of orders that are not delivered accurately (deliveries with wrong items and quantities) or not delivered on the agreed delivery date during a defined time period (Kannan and Tan, 2002; HPWQLD, 2014; USAID, 2010).
- **Supplier lead time variability:** Supplier lead time is the time that elapses between the time a supplier is received an order and the time the order is shipped (Siringoringo and Basri, 2009). This indicator measures the difference between quoted and actual supplier lead time in days (USAID, 2010). This indicator is calculated for each order of the suppliers. If a supplier delivers more than one order, the lead time variability for this supplier is calculated by taking the average of the differences for all of the orders in a specific time interval. A delay in the shipment of raw materials and other components causes delays in the production schedule and customer dissatisfaction.
- **Number of orders that do not meet quality specifications:** It represents the number of orders of a supplier that do not meet quality standards and the specifications in the contracts (USAID, 2010; HPWQLD, 2014). It is an indicator of suppliers' quality.
- **Commodity price variance:** This indicator is the percentage variance between contract unit price of the supplier and international reference unit price for a commodity (USAID, 2013).

9) Indicators of poor production planning and control: The following indicators can be used to detect, measure and monitor inaccuracy, inefficiency and delay risks in production planning and control activities.

- **Number of delayed orders:** It measures the number of delayed orders within a certain time period. It is one of the most important and basic indicators that is used to measure the performance level of the company to fulfill an order and customer dissatisfaction risk (Lian, 2006; Marr, 2012).
- **Sum of deviation of time against planned schedule of all active projects:** It is calculated by summing the deviations of time from the planned schedule in days for all active projects (orders) in the company (Keyes, 2016; Parmenter, 2007). It enables to compare the deviations from the target plans over time.
- **Difference between target and actual production lead time:** Production lead time is the time spent to produce an order (Mugwindiri et al. 2013). The difference between target and actual production lead time can result from a bad production plan or a problem in the manufacturing processes (e.g. breakdown of equipment, low operational performance etc.) (Lian, 2006; Parmenter, 2007). Violation of the target lead time causes delays in the delivery of the orders and hence cause customer dissatisfaction and loss of reliability.
- **Percentage of idle time per machine/equipment:** It is the percentage of non-productive time of machines/equipment within a certain time period (Parmenter, 2012; USAID, 2010). It represents the difference between theoretical capacity and the actual production performed in the current machine (McIntosh, 2017). The causes of idle time should be investigated.
- **Percentage of idle time per employee:** It is the percentage of non-productive time per employee within a certain working time. This indicator can be used to identify the risks of low workforce utilization rate and poor workforce planning performance (Dietrich, 2016).

10) Indicators of poor operational performance: This includes the risk indicators that aim to measure and track operational risks including failed or poor processes, machine breakdowns, employee performance, and operator error etc. (Davies et al., 2006; Parmenter, 2012).

- **Percentage of emergency maintenance:** This indicator is calculated by dividing the total number of hours spent for emergency maintenance in a given time interval to the total number of hours spent for planned maintenance activities in the same time interval (Parmenter, 2012; Davidson, 2013). Emergency maintenance refers to the time spent for unplanned maintenance and emergency repairs. A high percentage of emergency maintenance is an indicator of poor maintenance planning.
- **Total number of breakdowns:** Frequency of machinery or equipment breakdowns directly affect productivity and capacity utilization (Azizi, 2015). The company should record and monitor the total number of breakdowns or failures of machinery and equipment in a specific time period.
- **Downtime due to different types of machine/equipment failure (breakdown):** A breakdown of equipment or machinery cause loss of money and time for the company. Hence downtime resulting from breakdowns should be measured and tracked in order to take preventive actions for breakdown risk (Parmenter, 2007). The measurement of total breakdown time (in minutes and within a specific time period) according to different types of machines and equipment enables to identify the risky points and take proactive actions (Azizi, 2015).
- **Breakdown cost due to different types of machine/equipment:** Besides loss of time, breakdowns cause loss of money too. Therefore, breakdowns should also be evaluated based on their cost.
- **Manufacturing process quality measures:** The following risk indicators that are explained previously in the quality risk indicators part can be used to detect and measure the quality problems in the manufacturing processes: total number of defects observed in manufacturing processes, number of defects per causes, cost of quality correction as a percentage of sales revenue, and total time spent on quality improvement activities (Parmenter, 2007; Marr, 2012; La Londe, 2016; Dietrich, 2016).
- **Employee productivity rate:** This indicator is calculated by dividing the total output (value added) by the total number of employee (Esposito, 2015). It can be used to measure and track the efficiency of labor. The productivity will not be

measured per employee, because there is not a standard job and the time and effort required for the tasks changes due to projects.

- **Number of work related accidents:** It measures the total number of accidents per a given time interval (e.g. 100,000 working hours) (Mouatassim and Ibenrissoul, 2015; Dietrich, 2016; Parmenter, 2007). Accident statistics give information about the dangers in workplace and accident risk.

11) Logistics risk indicators: This category includes the indicators associated with transportation risks.

- **Percentage of late or inaccurate deliveries to customers:** It is the ratio of the total number of late or wrong deliveries in a period to the total number of deliveries in the same period (Lian, 2006; Davidson, 2013). Failure to meet the committed delivery date causes loss of customer satisfaction and reliability, and it may also bring penalty costs based on the contracts. This metric can be used to measure the risks of low delivery performance and customer dissatisfaction.
- **Average transportation cost per kilometer:** This indicator is measured by dividing the total transportation cost in a time period by the total number of transportation distance in the same period (USAID, 2010). It can be measured to track the trends in transportation costs. This indicator may also be calculated for different customer zones to identify high cost transportation regions.
- **Ratio of transportation cost to value of product:** This indicator is calculated by dividing the total transportation cost related with a vehicle, route, region or carrier (if the transportation process is outsourced) by the total value of product shipped within a specific time period (USAID, 2010). This ratio helps to discover inefficiencies in transportation planning, track increases in transportation costs as a percentage of the value of products, and also identify routes and regions with high transportation costs in proportion to the value of the shipped orders.

12) Indicators used to measure financial risks: Financial indicators are vital to measure the success of the company. Financial risk indicators tell the company whether they lose money or not (Marr, 2015). The company should use risk indicators that warn the company about a possible decline in profits or growth. Most of the financial risk

indicators (e.g. revenue, gross profit, net profit etc.) are measured and collected monthly by the accounting department. However they are not used in order to identify and assess risk exposures. There are various financial risk indicators. The following indicators are selected with interviews with the managers in the company. (Calculation of revenue, gross profit margin and net profit margin are explained previously in the indicators of poor sales performance part.) The following indicators give information about the financial health, business growth of the company and financial risk level.

- **Revenue:** Revenue is the income generated from business (sales of products or services) in a specific time period (Stoop, 2009; Matruglio and Tymmons, 2014).
- **Profit margins:** Different profit margins including gross profit margin, net profit margin and operating profit should be used while financial evaluations. The joint evaluation of these indicators gives additional information about the drivers of financial risks and helps to detect areas that need improvement (Marr, 2015; Dietrich, 2016). They can be used to detect a decrease in the profitability and sales performance of the company.
- **Cash flow solvency ratio:** It measures the ability of the company to meet its debts (Marr, 2015). It is calculated by dividing cash flow from operations by total liabilities (Marr, 2015). A decrease in cash flow solvency ratio indicates the emergence of a financial risk
- **Debt to capital ratio:** This indicator measures the ratio of debt to the total capital as a percentage (Investopedia, 2015). A large debt to capital ratio indicates a higher financial risk.
- **Asset utilization ratio:** It is calculated by dividing the total revenue in a specific period to the total value of assets of the company in the same period (McLean, 2003). This indicator represents the ability of the company to manage its assets to generate revenue.
- **Project cost variance:** This indicator is computed by calculating the difference between the planned budget (cost) and the actual budget of a project (Marr, 2012). A negative value indicates an over budget situation.

Financial risk indicators may be measured by product, service or business unit (Marr, 2015). This approach will help to discover and understand risky areas for the company.

13) Indicators used to measure labor related risks: The following risk indicators can be used to measure and track human resources risks including customer dissatisfaction, poor working conditions, and resignation of an employee.

- **Employee turnover rate:** A high employee turnover rate may be a sign of different risks including low employee satisfaction, lack of motivation and poor working condition (Stillwagon, 2015). It may also increase other risks such as poor employee performance and human error in operations (IOR, 2010).
- **Employee dissatisfaction survey results:** The results of the survey can be used to identify the issues that lead to customer dissatisfaction. These surveys can be used as an indicator of the following related risks: lack of motivation, loss of a key staff, and poor working conditions (Parmenter, 2012). Also by using the results of the surveys, an overall employee satisfaction index may be calculated in order to measure and track the overall satisfaction level of the employee (Marr, 2012).
- **Percentage of key staff without alternatives:** This indicator measures the risk of losing a key staff member (Chapelle, 2013). The personnel whose position cannot be filled by another staff member creates a risk for the sustainability of the business (Scandizzo, 2005; Teau and Protopopescu, 2015).

14) Indicators of Information System failures and inefficiency: Failure of information system or technology disrupts the business of the company. Two basic indicators are proposed to measure and monitor inadequacy and failures in information systems: number and duration of the failures.

- **Number of Information System failures:** This indicator represents the total number of information system failures in a specific time interval (Mouatassim and Ibenrissoul, 2015). A high number of failures and an increasing trend in the number of failures may be a sign of an inadequate information system and technology or the poor performance of the IT staff.
- **Information System downtime ratio:** In addition to the number of information system failures, the length of the downtime resulting from these failures is

another important indicator to measure the information system risk. This indicator represents the unavailability of the information system (Scandizzo, 2005). It is calculated by taking the ratio of the time period that a system fails to perform its function to the total time (Mouatassim and Ibenrissoul, 2015).

The identified risk indicators are linked to at least one key risk type in the company (Mouatassim and Ibenrissoul, 2015). It was hard to determine the risk-related data in the company, because the company does not collect key performance and risk indicators. They even do not measure the delivery delays. They only update the delivery date. The company does not have an ERP system and most of the collected information about the processes of the company are stored in papers and folders. In addition, there is not a performance measurement system in both operational and business levels. However, negotiations are held with ERP vendors, but this transformation period is a complex, hard and long-term project. The identified risk factors and risk indicators will be used in developing a data warehouse for the company. Design and development of a data warehouse is a time consuming process and requires a high level of expertise in this area. Therefore, the proposed DM-based structure and the studies in Section 6.3, 6.4 and 6.5 will be the basis of a large-scale project.

6.5. Assessments and Prioritization of the Risks

Some of the risks in Section 6.3 are selected as the most critical risks for the company. This selection is made by discussions with the business development engineer and interviews with the staff from various functional areas in the company. A risk evaluation form is applied in order to assess threat domains and understand the distribution of risks within the SC network by using expert opinions. This form helps to identify the risk profile of the company, departments, and its functions, and also give empirical evidence and insights for the selection of the DM application area. The results of the evaluation form is used in determining the risk problem that is subject to DM.

The risk evaluation form is given in Appendix A and applied to 11 participants from different departments. SC risk factors are basically measured with their probability (or frequency), their impact and likelihood of being detected either before or after they occur (Bradley, 2014). Therefore first, respondents are asked to evaluate some of the

potential risks threatening their company according to their probability, consequences and the difficulty of detectability based on a ten-point Likert scale. The ratings presented by Selvan et al. (2013) and DrugRegulations (2015) are used for evaluations.

The number of respondents is very low and it is not meaningful to measure them according to their frequencies. Therefore, the ten-point Likert scale data is treated as interval data. The average of the ratings for probability, severity and detectability are calculated. Then the Risk Priority Number (RPN, overall risk point) for each risk factor is calculated by multiplying these values. Table 6.2 represents the risk ratings for the top 20 risk types. Supplier quality problems, suppliers delivery issues, volatiles prices, customer payment problems and volatile exchange rate have the highest RPNs.

Table 6.2. Risk ratings based on experts' opinions

Risk Type	Average Values			
	Probability	Severity	Detectability	RPN
Supplier quality problems	7,73	8,00	4,18	258,51
Supply delivery problems	6,00	7,55	5,45	246,94
Volatile prices	6,64	7,09	5,18	243,85
Customer payment problems	6,18	7,73	4,55	217,13
Volatile exchange rate	6,55	7,18	4,27	200,85
Inadequate supplier management	5,82	6,36	5,09	188,49
Poor manufacturing planning and scheduling	5,27	6,00	5,55	175,44
Unavailability of qualified labor	6,18	6,18	4,55	173,70
Poor supply planning	5,00	6,45	5,18	167,23
High level dependence on suppliers	5,45	6,45	4,18	147,23
Ineffective Information System	5,64	6,18	4,18	145,71
Delayed payments from customers	5,00	6,45	4,27	137,89
Low performance of sales team	4,82	5,91	4,73	134,59
Poor operational performance	4,91	5,55	4,91	133,64
Capacity problems	5,27	5,27	4,64	128,90
Wrong feasibility studies	5,40	5,30	4,50	128,79
Contractual risks	5,36	6,36	3,73	127,22
Failures of Information Technologies and Systems	5,64	5,55	4,00	125,02
Product quality problems	4,64	5,73	4,45	118,28
Long design cycle time	5,18	4,73	4,73	115,80

Figure 6.2 represents the bar chart of the average RPNs of different risk categories. Supply risk category has the highest average value. The second most important risk category is financial risks according to the respondents' ratings.

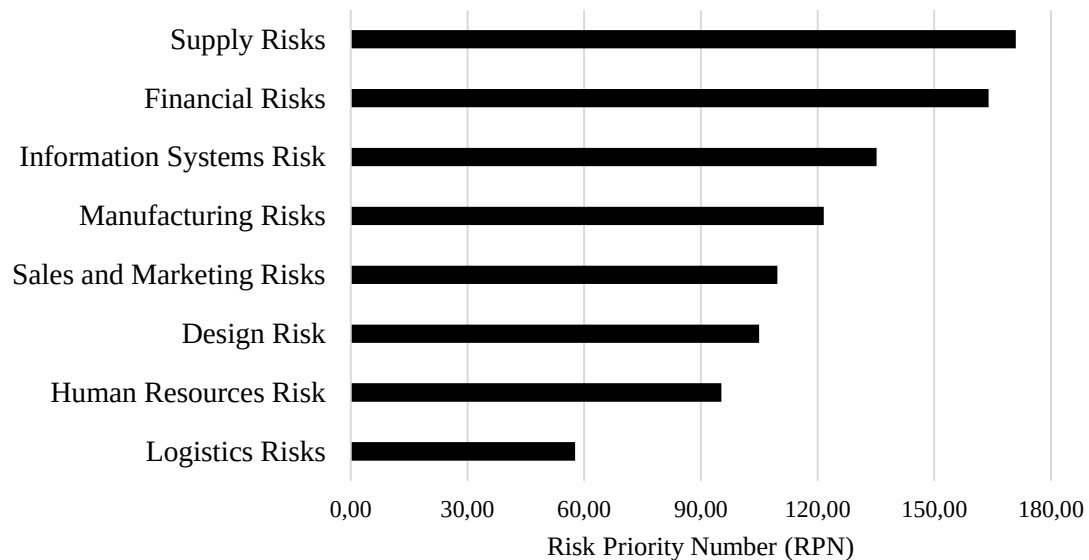


Figure 6.2. Average Risk Priority Numbers according to different risk categories

The bar chart in Figure 6.3 represents the ratings of different risk categories based on their probability, severity and detectability. The most frequent risks are determined as information systems, supply risks and financial risks. Financial risk category also has the highest value for its consequence. Based on detectability, supply risk category has the highest average value.

Based on the ratings of respondents and discussions with the managers in the company, supply risk category is selected as the subject of DM analysis. Figure 6.4 represents the probability, severity and detectability scores of the risks within supply risk category. Nearly most of the respondents gave ratings over 5 value for supply risks.

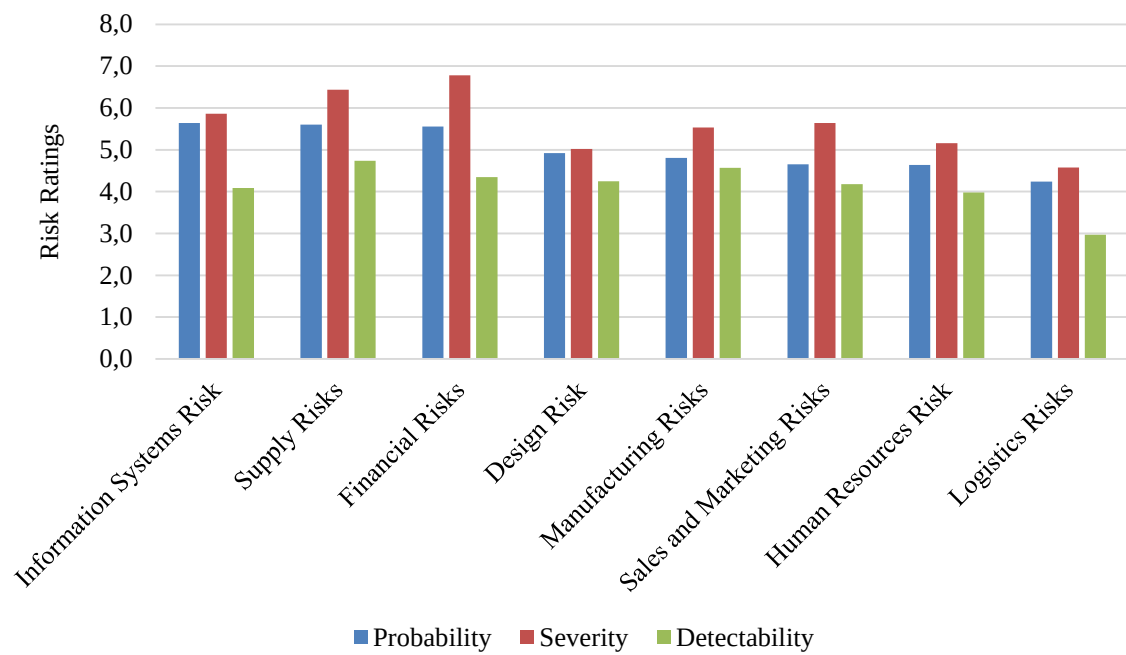


Figure 6.3. Ratings of Risk Categories

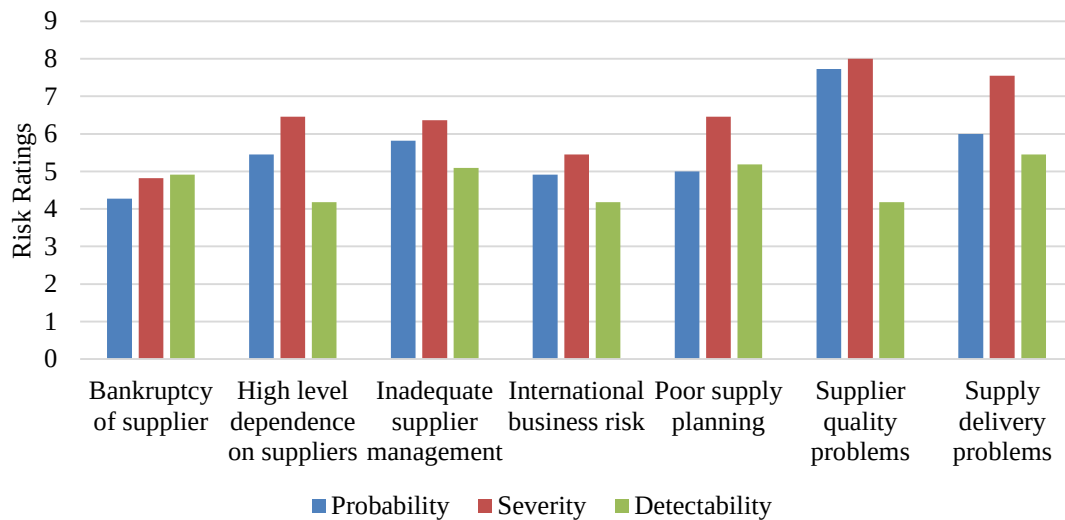


Figure 6.4. Ratings of the Different Supply Risk Factors

In addition, the respondents are asked to evaluate different operational functions of the company based on their risk exposure level on a ten-point Likert scale (1: low risk level, 10: high risk level). Table 6.3 represents the frequencies of different grades for each function. The aim of this table is to examine the risk levels of different departments. Figure 6.5 shows the average ratings of different operational functions with a spider-

web diagram. As it is seen from the figure, the most risky functions of the company are purchasing, sales and product/project design functions.

Table 6.3. Evaluation of the risk exposure level of different functions of the company

Functions	Points										Average
	1	2	3	4	5	6	7	8	9	10	
Sales				1	1	2	4		3		6,91
Marketing			1	3	2	4		1			5,18
Product/Project Design			1		2	1	3	3	1		6,64
Manufacturing		1			2	2	3	1	2		6,45
Production Planning	1	2		1	1	3	1	2			5,00
Purchasing				1	1	2		3	3	1	7,45
Packaging and Shipment	4	2	2	2				1			2,73
After Sales Service	1		2	4	3		1				4,09

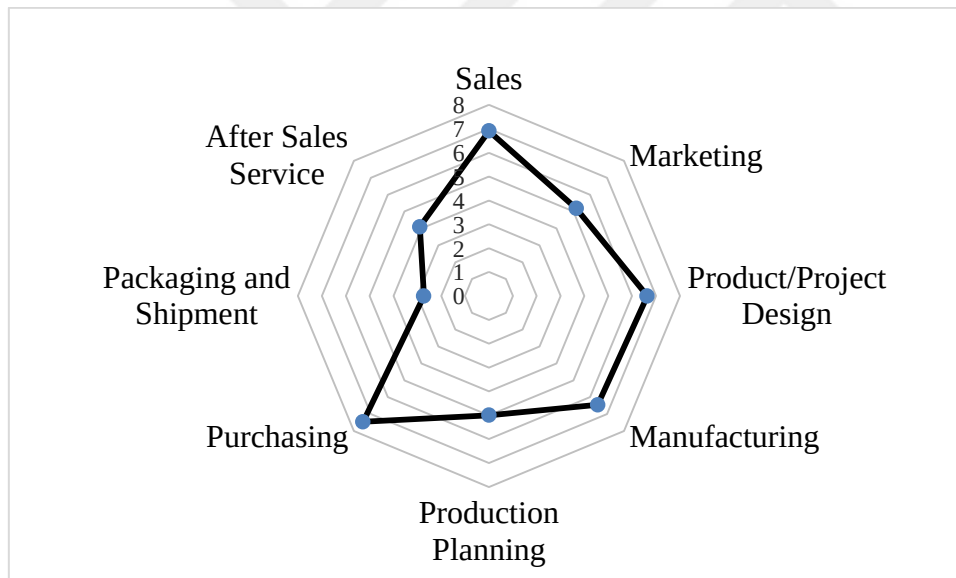


Figure 6.5 Spider-web diagram of the risk exposure levels of different operational functions

The company cannot measure and track all of the risks it is exposed to hence the most significant risks that threat the company are determined through discussions with management, interviews with the staff and a risk evaluation form applied in the company. The aim of this part is to identify the parts of the SC that are more vulnerable to disruptions. The results of this previous risk assessment step is used in the selection

of risk indicators and the identification of the risk problem that is subject to DM problem.

6.6. Decisions for the Implementation of DM Algorithms

We can use DM for the following issues: detect problems, identify relationships between risks and other factors (e.g. triggering factors), identification of the root causes of risks, filter noise data, clustering risky items, etc. This section includes the possible application areas of DM algorithms for SCRM in the current company. These application suggestions are determined based on field observations, interviews with personnel from different departments in the company, and studies in the previous sections. These alternatives areas are explored by using the guide questions in Section 5.5. and the risk assessments in Section 6.4. Application areas are categorized under different DM tasks and explained in the following.

Cluster analysis can be used to group items with similar risk and vulnerability attributes. The following studies can be done in this area:

- i) The company has a large number of suppliers. Suppliers have a critical importance due to the make to order strategy of the company. Suppliers can be clustered based on determined risk related criteria. Different supplier groups with different risk levels can be used in eliminating more risky suppliers or developing supplier development programs to mitigate supplier related risks.
- ii) The company generally sell high-value heavy machinery or complete plants and hence the number of repeat customers is low. Therefore, it is not reasonable to cluster customers considering their risk profile. However, the company has an increasing number of foreign customers and clustering analysis may be performed to group customer zones based on their risk exposure levels e.g. political risks, export restrictions, regulatory risk, terrorism etc. The company may focus on regions with less risk levels or develop different policies for risky customer zones.
- iii) Another alternative study is clustering products based on their risk profile. Products may be assessed according to different risk factors such as product complexity, manufacturing risk, average number of design changes, customer dissatisfaction ratings, quality problems, warranty risk, etc. The managers say

that the most risky products are manufactured for defense industry because of low tolerance levels in the quality of products. A clustering analysis may provide more reliable insights about the profile of risky products.

Classification is another alternative approach to group suppliers and market zones based on their risk profile. While clustering is an unsupervised learning technique, classification is supervised learning. In classification, there is a set of predefined classes and a new member is assigned to one of these classes.

Identification of the events that may lead to risks: Interesting and unusual patterns should be evaluated for the occurrence of a risk event (Liu et al., 2014). The reasons that cause to these patterns should be determined. Statistics, anomaly detection and association analysis may be used in this application area.

Association analysis can be used discover the relationships in the risk data. Various studies may be conducted to measure association between different risk indicators; e.g. association between low sales performance and customer dissatisfaction ratings. The first suggestion is to perform an association analysis on the relationship between employee dissatisfaction levels and employee characteristics. According to managers, loss of a key staff is one of the most important problems of the company, because the heavy machine sector suffers by the lack of qualified labor. The company makes a satisfaction survey to its employee each year. The survey includes 16 questions associated with the opinions and satisfaction levels of the employee on different issues such as sufficiency of training, working environment, occupational safety, communication with the management and lunch services etc. Answers of the employee to these questions are recorded. Three different points are assigned to the answers: 0, 5 or 10. An association analysis may be performed by using the results of the employee satisfaction survey and employee information records in the human resources department. This analysis can provide information about the relationships between characteristics of the employee and employee dissatisfaction level. This information can be used in new employee recruitment process to evaluate the applicants based on their dissatisfaction and quitting risks.

Prediction tools can be applied to predict risk factors and future risk data trends. Various techniques such as Support Vector Machine, decision tree and NN can be used

based on the data structure and the preference of the decision maker. The company may use prediction techniques to understand how their cash value, revenue and growth rate are effected by different risk factors including changes in commodity prices, exchange rate, energy prices, etc. Regression analysis can also be used to predict the values of continuous risk data. The company may use regression analysis especially in predicting financial risks to warn about a possible decline in profits and growth. Most of the financial performance indicators (e.g. revenue, gross profit, net profit etc.) are measured and collected monthly by the accounting department. However, they are not used in order to identify and assess risk exposures. As an example, business growth rate can be estimated by using sales win rate, customer churn rate, product market share, etc.

Clustering analysis is selected to develop several supplier groups with different risk attributes. The results of the analysis will assist the decision-making processes in supplier management. This application is identified based the results of the risk evaluation form applied in the company (see Section 6.3.2) and discussions with the staff from different functional areas and levels. The company has a make to order strategy and the performance of the suppliers has a high impact on the success of the company. Hence, an effective procurement and supplier management process considering supplier risk factors is vital for the success of the organization. Supplier risk is also one of the most common and most studied risks in the literature (Section 3.4). Therefore, this process is selected for the application of the DM algorithm.

Supplier evaluation and selection is one of the most critical and strategic processes in make to order SCs (Fang et al., 2016). The aim of this process is to maximize the overall value in purchasing (Er Kara et al., 2016). In today's competitive business life, companies generally select their suppliers mostly based on cost criteria. This increases the vulnerability of the SC and the number of supplier related risks. A problem in the supply of raw materials and parts can cause delays in production, financial losses, and customer dissatisfaction. Currently, the company select its suppliers based on the experience and judgements of the staff in purchasing department. Lack of an effective supplier evaluation and selection process is the most critical and risky issue in the purchasing department. The case study focuses on the adaption of SCRM to the supplier evaluation and selection process in order to reduce the supply risk.

5W1H technique is used to identify the details of the DM application:

- Why (Objective of the study): Develop supplier groups with different risk levels in order to assist in supplier selection and identification of supplier development programs.
- Where (Business Practices): DM tool will be applied in the purchasing department.
- What (Concept): A cluster analysis will be applied to groups suppliers based on their risk attributes.
- How (Method): A set of criteria will be determined in order to measure suppliers' risk levels and data will be collected for all of the suppliers that is subject to the analysis. Clustering algorithm will be applied on this data set.
- Who (People): The risk analysis and management team will perform the analysis. Two domain experts from the purchasing department will be incorporated to the team. One of them is responsible for the procurement processes and procedures. She has a close contact with suppliers. The other domain expert is a mechanical engineers and has a high level of expertise in technical issues about the supplied commodities and orders.
- When (Situation): The clustering application will be determined immediately.

6.7. Using Cluster Analysis to Evaluate Suppliers based on Their Risk Profile: A Case Study

An industrial case study is implemented to illustrate the applicability of the DM-based SCRM model. A set of suppliers are clustered based on various qualitative and quantitative risk criteria. First, the supplier-clustering problem is explained and the solution methodology to solve this problem is presented. Then, supplier risk assessment criteria are defined and weighted by using BWM. Cluster analysis is performed on the supplier risk data. Finally the results are given and discussed.

6.7.1. Problem definition and solution approach

Supplier evaluation and selection process is based on several traditional criteria in the case study company. However, the company may face significant supply risk problems by overlooking supplier related threats. Supplier related risks should be decreased at the

beginning of the procurement function by eliminating unreliable and risky suppliers. This can be achieved by considering risk levels of the suppliers for different risk types in this process. The aim of the case study is to propose a clustering-based model for supplier evaluation and selection problem considering supply risk. Suppliers will be clustered according to their risk profile. Supplier groups with different risk exposure levels and attributes will assist the supplier selection process for the selection of the suppliers with low risk levels. The results of the clustering analysis may also be used in the identification of supplier development programs.

Among different DM tasks, clustering is selected because of the following reasons:

- Clustering is more suitable to the structure of the supplier evaluation and selection problem. This problem includes the assessment and selection of suppliers based on some predetermined criteria. Clustering helps to group suppliers with similar characteristics and the created supplier segments can be used to eliminate supplier groups that do not provide the desired specifications.
- Suppliers have a high importance for the company. Clustering provides the opportunity to have a group of alternative suppliers. If the company has to find a new supplier, pre-determined supplier segments will help to find an alternative supplier with similar characteristics immediately.
- The company considers some traditional criteria in the supplier evaluation and selection process; e.g. quality, delivery performance, service quality etc. However, companies have to consider risks and threats related with suppliers in their purchasing decisions (Entchelmeier et al., 2006). These risks may have very serious disruptive consequences for the company. Clustering suppliers based on some determined risk criteria helps to eliminate risky suppliers. The company may select a supplier based on various criteria from the supplier cluster that has the lowest risk values.
- There are a myriad of different supply risks and it is very hard to find meaningful patterns within such a complex structure. Clustering is a powerful and efficient tool to learn about complex data sets (Berry and Linoff, 2004).
- The company has a high number of suppliers and it increase the effort, time and cost required to select a proper supplier. Clustering helps to gain a manageable number of suppliers (Şahin and Supçiller, 2015)

Figure 6.6 represents the flow chart of the case study. There are ten main steps in the proposed model.

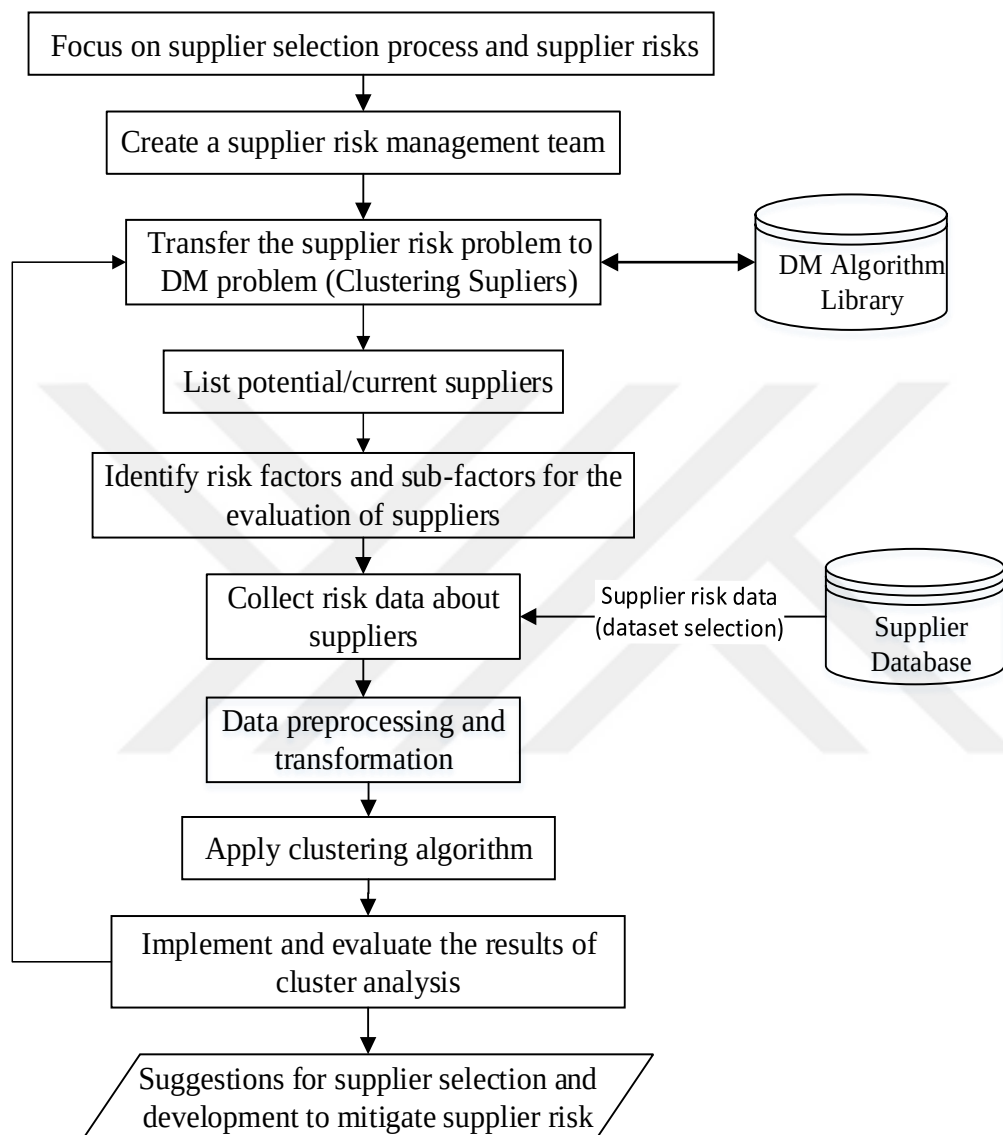


Figure 6.6. Flowchart of the case study

After the identification of the risk problem (grouping suppliers with similar risk attributes), a risk analysis and management team is determined for supply risk management problem. This team constitutes of five people and three of them will take part in the evaluation of risk criteria and assessment of suppliers based on the selected criteria. Risk analysis and management team members are presented in the following:

- i) Risk management director: Business development engineer was assigned as the risk management director of the company. She is responsible for the coordination and management of the activities in the proposed model.
- ii) Manager: Commercial manager (Decision maker 1) of the company has a high effect on the selection of suppliers. He has a high authority in the determination of SC stakeholders and makes regular field visits both to foreign and local suppliers. He has a high expertise about the sector of suppliers and the general conditions (facility, technology level etc.) of suppliers.
- iii) Domain experts: There are two domain experts from the purchasing department. One of them (Decision maker 2) has a high expertise in the procurement processes and has a closer contact with suppliers. The other domain expert (Decision maker 3) has a technical expertise and has a high knowledge in engineering related issues such as manufacturing processes, technological capability of suppliers, and quality level etc.
- iv) Data mining expert: The writer of this thesis will take part as a DM expert in the supply risk team. She takes part in all processes of the case study and she is responsible for the analysis of the supplier risk data.

The main and best-selling product of the company is mills. In addition, the production of mills requires working with a higher number of suppliers. Therefore, the suppliers of the core parts of a mill are selected for the clustering analysis. The most of the suppliers of the company are national firms. There are small, medium and large-sized suppliers. Totally 72 key suppliers are identified as the most critical suppliers of the company and selected for the analysis. 69 of them are domestic and 3 of them are overseas. Supplier ID number is assigned to all of the suppliers. Some of the selected suppliers produce different products. This is one of the limitations of the case study due to the total number of suppliers of the company. 72 suppliers will be evaluated using qualitative and quantitative risk-related criteria. First, a set of criteria is determined by using the literature review in Section 4.4.3 and interviews with the members of the supplier risk analysis and management team. Then, the final set of criteria is identified by discussions with the business development engineer. The weights of the risk criteria are determined by using the BWM that is proposed by Jafar Rezaei (Rezaei, 2015; Rezaei, 2016). First, the best (most desirable or important) and worst (least desirable or least important)

criteria are selected among a set of criteria. Then, the decision maker evaluates the preference of the best risk criterion and worst criterion over the other risk criteria respectively. Figure 6.7 represents the comparison of the best and the worst criteria to the others (reference comparisons).

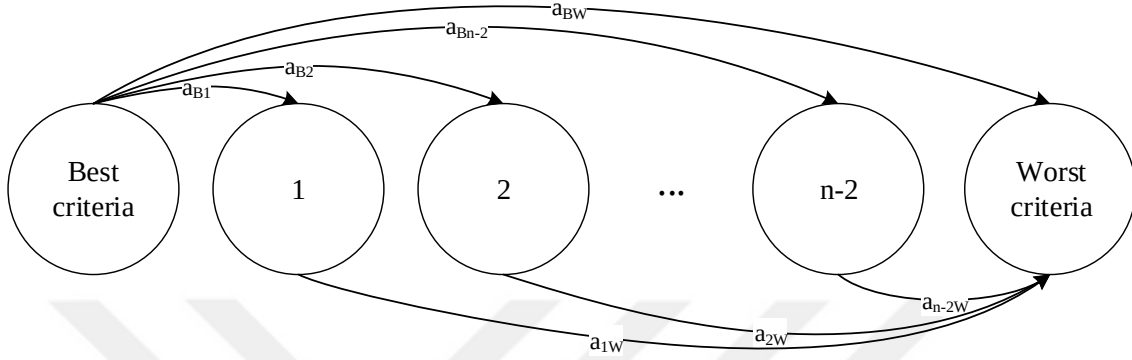


Figure 6.7. Comparison of the best and worst criteria to the others (adapted from Rezaei, 2015)

The decision maker determines the preference of the best risk criterion over all the other risk criteria using the given scale. It generates the Best-to-others vector for each decision maker:

$$A_B = (a_{B1}, a_{B2}, \dots, a_{Bn})$$

where a_{Bj} represents the preference of the best criterion B over criterion j . The value of the a_{Bj} will be equal to 1 if criterion j is the best criterion ($a_{BB} = 1$).

Then the decision maker determines the preference of all the other criteria over the worst criterion using the same scale. This generates the Others-to-worst vector for each decision maker:

$$A_W = (a_{1W}, a_{2W}, \dots, a_{nW})^T$$

where a_{jW} represents the preference of the criterion j over the worst criterion W . The value of the a_{jW} will be equal to 1 if criterion j is the worst criterion ($a_{WW} = 1$). Due to the reciprocal property of the pairwise comparison matrix, totally $(2n-3)$ pairwise comparisons are conducted by the decision maker.

The next step is calculating the optimal weights $(w_1^*, w_2^*, \dots, w_n^*)$ by using the evaluations of the decision makers. The optimal weights for the risk criteria satisfy the following conditions: i) $w_B/w_j = a_{Bj}$ and ii) $w_j/w_W = a_{jW}$. Therefore we need to minimize the maximum absolute differences $\left| \frac{w_B}{w_j} - a_{Bj} \right|$ and $\left| \frac{w_j}{w_W} - a_{jW} \right|$ for all j . All of the weights should be nonnegative and the sum of the weights should be equal to 1. This problem can be formulated as follows (Rezaei, 2015):

$$\begin{aligned}
 & \min \max_j \left\{ \left| \frac{w_B}{w_j} - a_{Bj} \right|, \left| \frac{w_j}{w_W} - a_{jW} \right| \right\} \\
 & \text{s.t.} \\
 & \sum_j w_j = 1 \\
 & w_j \geq 0, \text{ for all } j
 \end{aligned} \tag{1}$$

Rezaei (2016) converted the model (1) to the following linear problem:

$$\begin{aligned}
 & \min \varepsilon \\
 & \text{s.t.} \\
 & |w_B - a_{Bj}w_j| \leq \varepsilon, \text{ for all } j \\
 & |w_j - a_{jW}w_W| \leq \varepsilon, \text{ for all } j \\
 & \sum_j w_j = 1 \\
 & w_j \geq 0, \text{ for all } j
 \end{aligned} \tag{2}$$

The optimum values of ε^* and the weights $(w_1^*, w_2^*, \dots, w_n^*)$ are obtained by solving problem (2). The linear version of the BWM is used in the case study (Rezaei, 2016). BWM, which is a MCDM method is selected for several reasons (Rezaei, 2015; Rezaei et al., 2015);

- i) A high number of risk criteria is determined in order to increase the efficiency of clustering analysis and broaden the scope of the analysis on the risk behavior of suppliers. Therefore, it will be difficult to weight these criteria by using traditional MCDM methods such as AHP, ANP and TOPSIS. BWM first determines the best (most important) and worst (least important) criteria and

compares them with other criteria. Hence the comparison process in BWM is less complex than the other MCDM methods.

- ii) BWM is a vector-based method, hence it requires a less number of comparisons than matrix-based MCDM methods. BWM requires $2n-3$ comparisons.
- iii) It is difficult to assign a number to express the preference between different criteria. It is the most critical factor that lead to inconsistency. BWM simplifies this pairwise comparison process and increase the consistency of the evaluations.

Three decision makers evaluated the 17 criteria based on the steps of the BWM, and then the weights are calculated by solving a linear mathematical model with GAMS. The final weights of the criteria are determined by taking the averages of the results of the three BWM solutions for each criteria.

The data on four quantitative criteria are gathered from the purchasing department. The evaluations on thirteen qualitative criteria are made by the three decision makers. Decision makers have different expertise, hence the evaluations of the three decision makers are also weighed by the business development engineer. The weighted scores of the suppliers are normalized in order to scale the data on the 17 criteria within a specific range.

The number of criteria is very high for cluster analysis, hence a factor analysis is applied to reduce the number of criteria. Cluster analysis is performed on the preprocessed data.

The analysis of the data is performed by using SPSS version 20. The results of the cluster analysis are interpreted with the risk analysis and management team. The knowledge gathered by the comments on the clusters will be used in selecting low-risk suppliers and/or develop supplier improvement programs.

This is the first study that applies cluster analysis to group suppliers according to their risk profile. In addition, this is the first time BWM and cluster analysis is performed together.

6.7.2. Supplier risk assessment criteria

Companies need to investigate, analyze and select their suppliers with several dimensions. These dimensions differ according to the current sector and requirements of the company. The effectiveness of the supplier evaluation and selection depends on the quality of the criteria identification process. The selection of supplier risk factors is also very important for the efficiency of the clustering algorithm, because supplier clusters will be created based on these factors. This section includes the identification of the supplier evaluation criteria concerning risk (risk criteria) and their definition.

In this study, we considered specific requirements and risk attitude of the company and the structure of the sector. First a set of risk evaluation criteria (risk types) for suppliers is determined through literature review (see Sections 3.4 and 4.4.3) and supply risks in the focal company that are determined in Section 6.3.1. Supplier evaluation and management criteria vary depending on the strategy and the need of the organization (Chan and Kumar, 2007). Hence, the final set of criteria is determined after several iterative and structured meetings and discussions with managers and purchasing staff in the case study company. The selected risk evaluation criteria for suppliers is represented according to risk categories in Figure 6.8.

The set of supplier evaluation criteria includes 17 different risk related criteria: $C=\{c_1, c_2, \dots, c_{17}\}$ that are grouped under 8 risk dimensions (categories). Four criteria include quantitative values related with different risks (c_4, c_8, c_{10} , and c_{11}). Thirteen criteria include qualitative evaluations of suppliers based on different risk types ($c_1, c_2, c_3, c_5, c_6, c_7, c_9$, and $c_{12}-c_{17}$). These criteria are used as an indicator of suppliers' risk potential due to different issues including poor performance, communication problems etc. It is difficult to convert some of the risk categories into measurable variables/indicators. In addition to operational risk types, one criteria related with catastrophic risks is also added to the study. The mixed set of risk criteria provides incorporating different aspects of supply risks and develop a comprehensive supplier evaluation.

The risk criteria that is used in the case study are given in Figure 6.8.

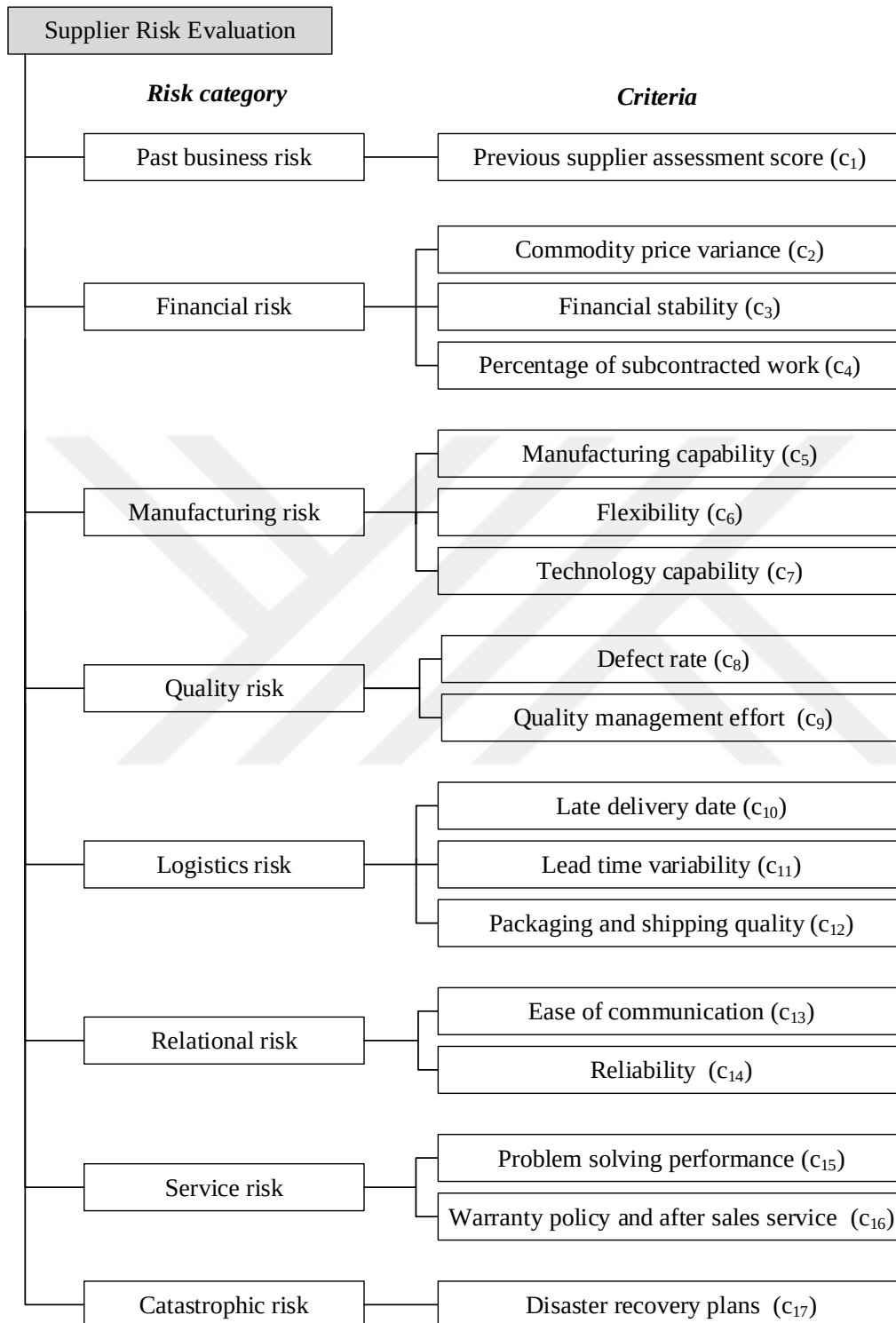


Figure 6.8. Main risk categories and risk types considered to assess suppliers

Supplier performance history

- 1. Previous supplier assessments (c_1):** This criterion refers to the previous assessments of the suppliers (Thanaraksakul and Phruksaphanrat, 2009; Lee, 2009). The current company make a supplier evaluation survey to the purchasing department for each purchasing activity of suppliers. The staff in the purchasing department have been evaluating all suppliers with a 1-5 scale for 11 years. The questions are updated in 2014. There are evaluations for 186 suppliers based on five criteria: quality system, process control, references, technological structure and delivery performance. All of the criteria have weights. We filtered the evaluations of the selected 70 suppliers. There are more than one evaluation for most of the suppliers, so we took the average of these ratings for each supplier and for each criteria. Then the weighted total points are calculated in order to use as an indicator of prior experience with the suppliers. It is an important indicator, which represents the historical performance and reliability of the supplier (Lee, 2009; Chen, 2011).

Financial risks

- 2. Purchase (commodity) price variance (c_2):** This indicator represents the level of the supplier's price within the standard sector price. "1" point represents a very low price, "5" represents an average value and "9" represents a high level of price. It represents the competitiveness of the price (Punniyamoorthy et al., 2011; Chan and Wang, 2013a).
- 3. Financial condition of the supplier (c_3):** This indicator represents the risk ratings of the supplier's financial condition by considering its economic status, dept structure, market share, annual revenue and growth, financial stability etc. (Chan and Kumar, 2007; Thanaraksakul and Phruksaphanrat, 2009; Chen, 2011; Punniyamoorthy et al., 2011). It is an indicator of poor financial health of the supplier (Kull and Talluri, 2008). Nine point indicates a high likelihood of supplier bankruptcy.
- 4. Percentage of supplier's work commonly subcontracted (c_4):** It is the ratio of the supplier's work that is subcontracted (Kannan and Tan, 2002; HPWQLD, 2014; Guertler and Spinler, 2015). Suppliers are dependent on their

subcontractors for this part of their job. Hence, a high level of subcontracting lead to a high level of uncertainty and risk exposure.

Manufacturing (performance) risk

5. **Manufacturing capability (c_5):** This indicator refers to the rating of the supplier's manufacturing capability in terms of the conditions, qualification, adequacy and capacity of production facility, machines, equipment and the employee of the supplier. (Thanaraksakul and Phruksaphanrat, 2009). The focal company visits and evaluates its potential suppliers for an initial observation. They also make regular visits during their orders. This rating is identified by using the evaluations and observations during these field visits.
6. **Flexibility (c_6):** Supplier flexibility can be defined as the ability of the supplier to respond to changing demands and requirements of customers (Kull and Talluri, 2008; Lee, 2009). Suppliers are rated based on their flexibility in terms of volume, product mix, product design and, delivery date. While 1 point represent a high level of flexibility of the supplier, nine point indicates that the supplier is lack of flexibility.
7. **Technological capability (c_7):** It is a measure of the capability and robustness of supplier's technological systems and used to measure technology risk (Chan and Wang, 2013a; Govindan et al., 2015; Heidarzade et al., 2016). It considers the manufacturing technology and R&D capability of the supplier. Nine point indicates that the suppliers has a low level of technological capability and is unable to respond to technological needs and innovations.

Quality risk

8. **Average defect rate of the supplier (c_8):** Defect rate is the proportion of the number of products that do not meet quality specifications to the total number of units supplied from the supplier (Nekoie et al., 2015; Guertler and Spinler, 2015). It is calculated by using the past data. If there are more than one purchasing (and quality inspection) record for the supplier, this indicator is calculated by taking the average of the records in the last five years. Noncompliance to quality specifications is an indicator of poor quality.

- 9. Quality management effort (c_9):** It refers to the rating of the supplier based on its quality efforts (commitment to quality). The following issues are considered during assessments of suppliers; quality-related certificates, quality control activities, capability of quality management systems, quality improvement programs, recording of quality inspections etc. (Paul, 2015; Govindan et al., 2015). Nine point indicates that there is a lack of quality management efforts and programs.

Logistics risks: The following indicators are used to measure delivery reliability.

- 10. Late delivery rate of the supplier (c_{10}):** It is the ratio of the number of late deliveries to the total number of orders (Wu and Olson, 2008; Chan and Wang, 2013a). This indicator is calculated by using the past records.
- 11. Supplier lead time variability (c_{11}):** This indicator is measured by dividing the difference between quoted and actual supplier lead time by the quoted lead time (in days). It is an indicator of the variation from promised delivery lead time.
- 12. Packaging and shipping quality (c_{12}):** This indicator refers to the risk ratings of the supplier's packaging and shipping functions both in terms of quality of this function and compliance to standards (Thanaraksakul and Phruksaphanrat, 2009; Punniyamoorthy et al., 2011). Nine point indicates that the supplier has a low level of packaging and shipping quality and it is likely to have a problem associated with appropriateness in packaging and shipping.

Relational risks

- 13. Ease of communication (c_{13}):** This indicator refers to the overall communication rating of the supplier. It considers problems and difficulties in communicating with suppliers (Kull and Talluri, 2008). These problems include unstable and inefficient communication networks, difficulty to reach contact persons/ sales representatives (e.g. unavailability or discontinuity of the responsible person), misinterpretation of the emails by suppliers, imprecise and slow communication manner, lack of transparency, unwillingness and privacy for information sharing (Chen, 2011; Yücenur et al., 2011; Guertler and Spinler, 2015). This indicator helps to identify failures in communication and coordination with suppliers.

14. Reliability (c₁₄): It represents the reliability level of the supplier based on compliance to contract terms and conditions in previous businesses, accuracy and reliability of documentation and information provided by suppliers, reputation in the sector, and references. Level of trust in the buyer-supplier relationship is a very important factor that effects strength of business relationships and information sharing (Punniyamoorthy et al., 2011).

Service risks

15. Problem solving performance (c₁₅): This indicator represents the risk level arising from ineffective and poor sales and technical support. Problem solving performance includes the response time of suppliers to a complaint, quality concern or emergency problem, problem solving capability, handling of complaints, technical support level, and remedy to correct a quality problem (Chan and Kumar, 2007; Punniyamoorthy et al., 2011; Chan and Wang, 2013a). Nine point represents the irresponsiveness of the supplier.

16. Warranty policy and after sales service (c₁₆): This indicator refers to the rating of the supplier's after sales service and warranty & claim policy (in terms of coverage of warranty and service agreements, warranty period and satisfaction about claims) (Cheraghi et al., 2004; Thanaraksakul and Phruksaphanrat, 2009).

Catastrophic risks

17. Disaster recovery plans to deal with major disruptions (c₁₇): This indicator refers to the score of a supplier based on its disaster recovery plans. Most of the suppliers are located in a close region. Hence it is not meaningful to rank suppliers according to their risk exposure level for catastrophic risks such as earthquake, tsunami etc. Inadequate disruption management systems increase the risk exposure levels of companies (Paul, 2015). Effective disaster recovery plans can increase the robustness of suppliers to catastrophic events.

We collected data for 72 suppliers that supply critical raw materials and parts required to produce a mill. These suppliers do not produce the same product. This is a limitation of the data set. Therefore, we used expert evaluations for some criteria to cope with this limitation. As an example, risks associated with technical problem solving capability of

suppliers cannot be evaluated by using the number of days spent to solve unexpected problems, because it is dependent on the complexity of the product supplied by the supplier (Chou and Chang, 2008). Four quantitative criteria (c_4 , c_8 , c_{10} , and c_{11}) are typical numbers, averages and percentages. The values of the other thirteen criteria (c_1 , c_2 , c_3 , c_5 , c_6 , c_7 , c_9 , and c_{12} - c_{17}) are determined by subjective evaluations of the three decision makers in the risk management team.

6.7.3. Weighting of the risk criteria by using Best-worst Method

The three decision makers made their evaluations on risk-related criteria individually according to the BWM of Rezaei (2016). First, all of them has chosen the best (most important) and worst (least important) criteria among the 17 criteria which are explained in Section 6.4.2. Their choices for the best and worst criteria are given in Table 6.4.

Table 6.4. The best and worst risk criteria identified by decision makers

Decision makers	Best criteria	Worst criteria
Decision maker 1	Commodity price variance (c_2)	Percentage of subcontracted work (c_4)
Decision maker 2	Manufacturing capability (c_5) and commodity price variance (c_2)	Percentage of subcontracted work (c_4)
Decision maker 3	Reliability (c_{14})	Disaster recovery plans (c_{17})

Each decision maker determined the preference of their best criterion over all other criteria by using the nine-point scale that is given in Table 6.5. Then they determined the preference of all the criteria over their worst criterion by using the same scale.

Table 6.5. Nine-point pairwise comparison scale used in the Best-worst method (adapted from Schoenherr et al., 2008 and Saaty, 2008)

Intensity of importance	Verbal meaning for risk criteria comparison
1	Equally important
2	Equally to moderately more important
3	Moderately more important

Table 6.5. Nine-point pairwise comparison scale used in the Best-worst method (adapted from Schoenherr et al., 2008 and Saaty, 2008) (continues)

4	Moderately to strongly more important
5	Strongly more important
6	Strongly to very strongly more important
7	Very strongly more important
8	Very strongly to extremely more important
9	Extremely more important
Reciprocals of above	If one of the above values is assigned for the importance of a risk criteria i to j, then the importance of criteria j to i will take the reciprocal value.

Pairwise comparisons of the three decision makers for the best and worst criteria are given in Table 6.6.

Table 6.6. Pairwise comparisons of the decision makers for the best and worst criteria

	Decision maker 1		Decision maker 2		Decision maker 3	
Criteria	Best criterion: c₂	Worst criterion: c₄	Best criterion: c₅	Worst criterion: c₄	Best criterion: c₁₄	Worst criterion: c₁₇
c₁	4	7	6	3	3	8
c₂	1	9	1	9	3	7
c₃	3	7	9	2	4	5
c₄	9	1	9	1	8	2
c₅	6	7	1	8	2	8
c₆	8	4	2	7	5	6
c₇	6	7	2	6	1	9
c₈	2	9	4	4	2	8
c₉	5	7	2	8	6	5
c₁₀	2	8	3	7	2	7
c₁₁	2	8	3	6	2	8
c₁₂	3	5	2	7	2	8
c₁₃	5	5	4	6	4	6
c₁₄	4	4	2	8	1	9
c₁₅	3	6	2	8	1	9
c₁₆	5	5	2	8	1	9
c₁₇	8	3	2	8	9	1

Due to the reciprocal property of the pairwise comparison matrix, totally 31 $(2n-3)$ pairwise comparisons were conducted by each decision maker. As you can see from the table, the preference of a criterion to it gets the value of 1.

BWM model (Problem 2 in Section 6.7.1) is solved for each decision maker separately. The linear BWM problems are solved in GAMS. The screenshot of GAMS for the first BWM problem is given in Figure 6.9 (based on the preferences of decision maker 1).

```

Sets
j indice of the criteria /1*17/;
Variables
w(j) weight of the jth criteria
k objective function value for the linear model
z objective function;
Parameters
m(j) the preference of the best criterion over criterion j /1 4,
2 1, 3 3, 4 9, 5 6, 6 8, 7 6, 8 2, 9 5, 10 2, 11 2, 12 3,
13 5, 14 4, 15 3, 16 5, 17 8/
n(j) the preference of the jth criterion over the worst criterion /1 7,
2 9, 3 7, 4 1, 5 7, 6 4, 7 7, 8 9, 9 7, 10 8, 11 8, 12 5, 13 5,
14 4, 15 6, 16 5, 17 3/
Positive variables
w;
Equations
objective
constraint1
constraint2
constraint3
constraint4
constraint5;
objective.. z =e= k;
constraint1(j).. w("2")-m(j)*w(j) =l= k;
constraint2(j).. -w("2")+m(j)*w(j) =l= k;
constraint3(j).. w(j)-n(j)*w("4") =l= k;
constraint4(j).. -w(j)+n(j)*w("4") =l= k;
constraint5.. sum(j, w(j)) =e= 1;
model BWMerve/all/;
solve BWMerve using LP minimizing z;
display j, w.l, z.l;

```

Figure 6.9. Screenshot of GAMS for the first BWM problem

Solving the models for each decision maker, we gain the optimal weights that are given in Table 6.7.

Table 6.7. Weights of the risk criteria according to three BWM applications

	Decision makers				Decision makers		
Weights of the criteria	1	2	3	Weights of the criteria	1	2	3
w_1^*	0.050	0.023	0.045	w_{10}^*	0.100	0.046	0.067
w_2^*	0.152	0.122	0.045	w_{11}^*	0.100	0.046	0.067
w_3^*	0.067	0.015	0.034	w_{12}^*	0.067	0.069	0.067
w_4^*	0.012	0.010	0.017	w_{13}^*	0.040	0.035	0.034
w_5^*	0.033	0.111	0.067	w_{14}^*	0.050	0.069	0.108
w_6^*	0.025	0.069	0.027	w_{15}^*	0.067	0.069	0.108
w_7^*	0.033	0.069	0.108	w_{16}^*	0.040	0.069	0.108
w_8^*	0.100	0.035	0.067	w_{17}^*	0.025	0.069	0.009
w_9^*	0.040	0.069	0.022				

The objective function values (ε) for the three problems are as follows: $\varepsilon_1=0.048$, $\varepsilon_2=0.028$, and $\varepsilon_3=0.027$. All of these values are close to 0, hence the comparisons of the three decision makers can be accepted as consistent. The final weights of the criteria are calculated by taking the averages of the values in Table 6.7. Table 6.8 represents the values of the 17 criteria. These weights will be used in calculating the weighted values of the criteria for each supplier.

Table 6.8. Averages of the weights of the three BWM solutions

Weights of the criteria	Values	Weights of the criteria	Values	Weights of the criteria	Values
w_1^*	0,0393	w_7^*	0,0700	w_{13}^*	0,0363
w_2^*	0,1063	w_8^*	0,0673	w_{14}^*	0,0757
w_3^*	0,0387	w_9^*	0,0437	w_{15}^*	0,0813
w_4^*	0,0130	w_{10}^*	0,0710	w_{16}^*	0,0723
w_5^*	0,0703	w_{11}^*	0,0710	w_{17}^*	0,0343
w_6^*	0,0403	w_{12}^*	0,0677		

6.7.4. Supplier risk data

This section includes the collection of data on suppliers with respect to predetermined risk factors. Suppliers are assessed based on 17 risk related criteria. Four criteria are quantitative and thirteen criteria are qualitative. Quantitative criteria are: c_4 , c_8 , c_{10} and c_{11} . These criteria are ratios. Qualitative criteria are: c_1 , c_2 , c_3 , c_5 , c_6 , c_7 , c_9 , c_{12} , c_{13} , c_{14} , c_{15} , c_{16} and c_{17} . Criterion c_1 is calculated by taking the weighted average of previous subjective evaluations. Suppliers are rated based on five criteria after each order with an ordinal scale from 1 to 5 (1: high performance and 5: low performance). These criteria are quality system, process control capability, references, technological structure and delivery performance. The weights of the criteria are 0.15, 0.15, 0.05, 0.05, and 0.60 respectively. The weighted averages of the rating are used as an indicator of past business risk.

The values of criteria c_2 , c_4 , c_8 , c_{10} and c_{11} are gathered from decision maker 2 who has the main responsibility from the purchasing department. The values of the remaining qualitative criteria are identified by the three decision makers. Suppliers are assessed based on thirteen risk types by using a nine-point ordinal Likert scale. Various researchers treat ordinal values as interval data (Matook et al., 2009; Malhotra, 2007). Similarly, the supplier risk ratings for the thirteen qualitative criteria are assumed as interval in this study.

Three decision makers rated suppliers based on eleven qualitative criteria by using a nine-point Likert scale that is given in Table 6.9. One represents extremely low and negligible risk level. Nine represents an extremely high and serious risk level. The data on the twelve criteria are gathered from decision makers by conducting three sessions. Sessions have been done with each decision maker individually. Each session was performed in a different week and suppliers were assessed based on four criteria in each session. The data on criteria 2, commodity price variance is gathered only from decision maker 2, because she is responsible for gathering price quotation.

As explained in Section 6.4.1., each decision makers have different levels of knowledge, expertise and experience. In addition, they communicate by these suppliers based on different issues based on their responsibilities. Hence, first different weights are assigned for the ratings of the decision makers for each criteria. The weights are

given in Table 6.10. These weights are assigned with the manager and the work development specialist who is an industrial engineer.

Table 6.9. Nine-point Likert scale used in rating suppliers (adapted from Saaty, 2008)

Risk Rating	Verbal meaning
1	Extremely low and negligible risk level
2	Very low risk level
3	Low risk level
4	Slightly low risk level
5	Moderate risk level
6	Slightly high risk level
7	High risk level
8	Very high risk level
9	Extremely high and serious risk level

Table 6.10. Weights of the evaluations of decision makers for different criteria

No.	Criteria	Decision makers		
		1	2	3
1	Financial condition of the supplier (c ₃)	0.6	0.3	0.1
2	Manufacturing capability (c ₅)	0.3	0.2	0.5
3	Flexibility (c ₆)	0.2	0.4	0.4
4	Technological capability (c ₇)	0.3	0.2	0.5
5	Quality management effort (c ₉)	0.2	0.4	0.4
6	Packaging and shipping quality (c ₁₂)	0.2	0.4	0.4
7	Ease of communication (c ₁₃)	0.2	0.5	0.3
8	Reliability (c ₁₄)	0.2	0.4	0.4
9	Problem solving performance (c ₁₅)	0.2	0.4	0.4
10	Warranty policy and after sales service (c ₁₆)	0.2	0.4	0.4
11	Disaster recovery plans (c ₁₇)	0.6	0.2	0.2

The weighted averages are calculated for the eleven criteria that is given in Table 6.10. After the collection of the data on all of the seventeen criteria, the next step is data description part. Descriptive statistics is important for the selection of preprocessing and clustering algorithms. The descriptive statistics of the seventeen risk types are given in Table 6.11.

Each risk factor has a different importance level for the company, hence all values are multiplied with the weight of the current criteria. The preprocessing process and the cluster analysis are performed on this weighted data set. As it is seen from Table 6.11, some of the variables are measured on different scales. Most of the clustering methods are sensitive to the scales and standard deviation of different variables (Hair et al., 2006), hence a standardization process is needed before measuring their similarity. The seventeen risk variables are converted to z scores and the standardized values will be used in latter analysis.

Table 6.11. Descriptive statistics of the seventeen risk types

Risk types	Min	Max	Range	Mean	Median	Mode	Standard deviation
c ₁	1,00	4,85	3,85	2,29	2,15	2,00	0,74
c ₂	3,00	9,00	6,00	6,53	7,00	7,00	1,52
c ₃	2,40	6,10	3,70	4,66	4,70	4,60	0,89
c ₄	0,00	1,00	1,00	0,40	0,20	0,20	0,38
c ₅	2,30	8,70	6,40	4,93	4,85	4,50	1,21
c ₆	3,00	8,00	5,00	4,89	4,80	4,40	0,85
c ₇	2,80	6,30	3,50	4,94	5,00	5,00	0,73
c ₈	0,00	0,50	0,50	0,15	0,10	0,10	0,11
c ₉	1,00	8,20	7,20	4,66	4,80	4,80	1,15
c ₁₀	0,00	0,70	0,70	0,16	0,10	0,10	0,14
c ₁₁	0,00	0,75	0,75	0,18	0,13	0,10	0,15
c ₁₂	2,80	8,60	5,80	5,62	5,60	6,40	1,04
c ₁₃	1,00	6,90	5,90	4,23	4,20	3,50	1,12
c ₁₄	2,00	8,80	6,80	4,62	4,40	4,40	1,16
c ₁₅	2,60	8,80	6,20	5,03	5,00	4,80	1,19
c ₁₆	1,40	8,80	7,40	5,03	5,00	5,40	1,23
c ₁₇	2,80	9,00	6,20	4,96	4,70	4,60	1,13

Cronbach's alpha is calculated in order to measure the internal consistency and reliability of the data set. It is considered to be a measure of scale reliability (Oktay

Firat, 2012). Cronbach' alpha for the 17 criteria is 0.845. This value is greater than 0.70, meaning that the suppliers have a relatively high internal consistency.

There are 17 supplier evaluation criteria, but clustering algorithms generally perform well with a less number of variables. Also as explained in Section 3.1, risk factors are interrelated. Therefore, a factor analysis is performed to examine the relationship between these criteria and group some of them. Factor analysis is a statistical technique that is used to analyze the structure of interrelationships (correlations) among variables and reduce a large number of variables into a less number of factors (Firat, 1996; Hair et al., 2006).

A correlation matrix is constructed based on supplier risk data and given in Table 6.12. The following issues are regarded to check the appropriateness of factor analysis (Malhotra, 2007; Firat, 1996): i) There is a high correlation between some of the risk types. For example; late delivery date and lead time variability: 0.961, problem solving performance and warranty policy & after sales service: 0.845, and flexibility and manufacturing capability: 0.719. ii) The data set includes more than 50 observations. iii) The ratio of the number of observations (sample size, 72) to the number of variables (17) is approximately four. Generally, at least four or five times is acceptable to most of the researchers.

Bartlett's test of sphericity and Kaiser-Meyer-Olkin (KMO) tests were used to test the appropriateness of factor analysis. The SPP output of the tests are given in Figure 6.10. The Bartlett's test is used to test the null hypothesis that the population correlation matrix is an identity matrix. As it is seen from Figure 6.10, the test statistic has a large value and the significance level is very low, hence the null hypothesis is rejected. It means that factor analysis is appropriate. KMO test measures the sampling adequacy. The KMO statistic for the supplier risk data set is 0.761 and greater than 0.5. This indicates that the correlations between pairs of risk variables can be explained by other variables and hence factor analysis is appropriate for this data set. Anti-image correlation matrix is also evaluated to assess the suitability of the variables for factor analysis (Oktay Firat, 2012). Most of the off-diagonals are small and the diagonals of all the variables except Criteria 2 are greater than 0.5. However, this criterion has a significant correlation with Criteria 4 in the correlation matrix. Therefore, we did not drop this variable.

Table 6.12. Correlation matrix of 17 risk criteria

Pearson Correlations																	
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17
C1	1	-,058	,157	-,152	,029	,131	,094	,283*	,156	,127	,128	,085	,103	,218	,211	,240*	,276*
C2	-,058	1	,127	,298*	-,097	,020	,057	-,103	-,130	-,027	,033	,067	,142	-,141	,088	,165	,216
C3	,157	,127	1	,066	,485**	,538**	,473**	-,010	,523**	-,056	-,009	,383**	,104	,324**	,203	,296*	,378**
C4	-,152	,298*	,066	1	-,110	-,081	-,004	-,202	-,195	-,127	-,095	-,015	,086	-,116	,046	,001	,027
C5	,029	-,097	,485**	-,110	1	,719**	,614**	,238*	,558**	,081	,109	,395**	,198	,442**	,347**	,311**	,404**
C6	,131	,020	,538**	-,081	,719**	1	,599**	,141	,632**	,044	,023	,408**	,235*	,456**	,449**	,473**	,403**
C7	,094	,057	,473**	-,004	,614**	,599**	1	-,064	,408**	-,197	-,151	,160	,350**	,283*	,234*	,229	,259*
C8	,283*	-,103	-,010	-,202	,238*	,141	-,064	1	,190	,821**	,828**	,206	,000	,208	,325**	,337**	,372
C9	,156	-,130	,523**	-,195	,558**	,632**	,408**	,190	1	,114	,075	,441**	,286*	,684**	,482**	,629**	,566**
C10	,127	-,027	-,056	-,127	,081	,044	-,197	,821**	,114	1	,961**	,194	-,019	,179	,346**	,361**	,417**
C11	,128	,033	-,009	-,095	,109	,023	-,151	,828**	,075	,961**	1	,186	-,034	,122	,344**	,327**	,437**
C12	,085	,067	,383**	-,015	,395**	,408**	,160	,206	,441**	,194	,186	1	,375**	,320**	,361**	,361**	,311**
C13	,103	,142	,104	,086	,198	,235*	,350**	,000	,286*	-,019	-,034	,375**	1	,211	,420**	,453**	,343**
C14	,218	-,141	,324**	-,116	,442**	,456**	,283*	,208	,684**	,179	,122	,320**	,211	1	,491**	,583**	,602**
C15	,211	,088	,203	,046	,347**	,449**	,234*	,325**	,482**	,346**	,344**	,361**	,420**	,491**	1	,845**	,790**
C16	,240*	,165	,296*	,001	,311**	,473**	,229	,337**	,629**	,361**	,327**	,361**	,453**	,583**	,845**	1	,804**
C17	,276*	,216	,378**	,027	,404**	,403**	,259*	,372**	,566**	,417**	,437**	,311**	,343**	,602**	,790**	,804**	1

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

KMO and Bartlett's Test	
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	,761
Approx. Chi-Square	835,258
Bartlett's Test of Sphericity	df
	136
Sig.	,000

Figure 6.10. SPSS output for Barlett's test and KMO

After checking the assumptions of the factor analysis and the results of the formal statistical tests, it shows that factor analysis can be performed in the supplier risk data set efficiently. PCA approach is selected for factor analysis and applied in SPSS 20. PCA considers the total variance in the data (Malhotra, 2007). Table 6.13 represents the total variances explained by different factors.

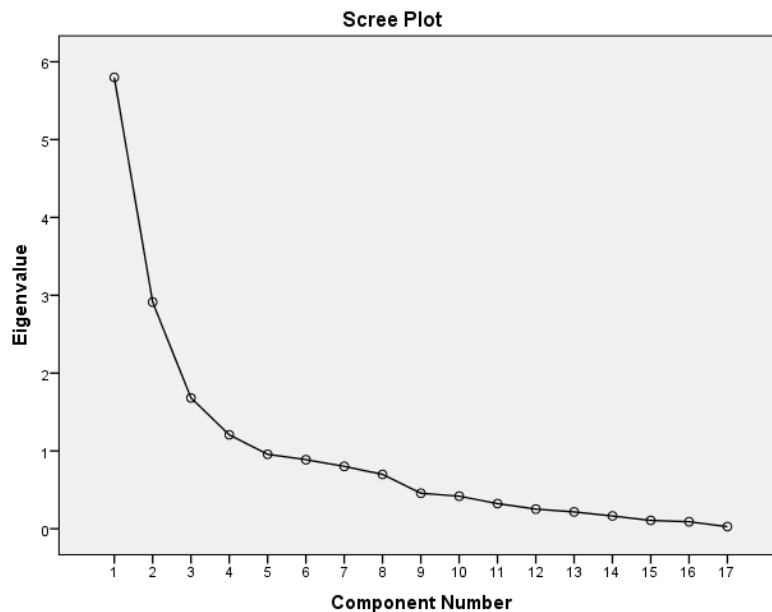
Eigenvalues represents the total variance explained by each factor. Eigen values decrease from factor 1 to factor 17. The total variance is equal to the number of variables, 17. The number of factors were determined based on eigenvalues. The factors with an eigenvalue greater than 1.0 are extracted (Kaiser Criterion). The four factors account for approximately 34%, 17%, 9.9% and 7% of total variance respectively. These four factors totally account for 68.225% of total variance (>65%).

Table 6.13. Total variance explained by different factors

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5,799	34,109	34,109	5,799	34,109	34,109	3,563	20,960	20,960
2	2,912	17,132	51,241	2,912	17,132	51,241	3,417	20,101	41,061
3	1,681	9,887	61,128	1,681	9,887	61,128	3,027	17,808	58,869
4	1,206	7,097	68,225	1,206	7,097	68,225	1,590	9,355	68,225
5	,957	5,628	73,853						
6	,888	5,222	79,075						
7	,802	4,718	83,792						
8	,698	4,108	87,900						
9	,457	2,688	90,588						
10	,418	2,462	93,049						
11	,323	1,900	94,949						
12	,253	1,486	96,435						
13	,217	1,276	97,711						
14	,164	,967	98,678						
15	,108	,633	99,311						
16	,090	,529	99,841						
17	,027	,159	100,000						

Extraction Method: Principal Component Analysis.

The scree plot in Figure 6.11 represents the eigenvalues plotted against the number of factors. As it is seen from the figure, a break occurs in four factors. Based on the eigenvalue criteria and the scree plot, four factors seem reasonable for supplier risk data.

**Figure 6.11.** Scree plot of eigenvalues

17 risk types are reduced to 4 factors. The risk types that have a correlational relationship are reduced to one variable or factor. The initial component matrix in Table 6.14 represents the unrotated factor loadings (correlations between the 17 risk variables and the 4 factors extracted) sorted by size.

The higher the absolute value of the factor loading, the higher the relationship. The interpretation of this grouping is not very reasonable. In addition, as it is seen from Table 6.14, the factors are correlated with many risk types.

Table 6.14. Initial component matrix

Component Matrix^a				
	Component			
	1	2	3	4
Zscore(C17)	,834	,148	,280	-,127
Zscore(C16)	,832	,095	,307	-,270
Zscore(C9)	,785	-,254	-,224	-,141
Zscore(C15)	,784	,121	,313	-,238
Zscore(C6)	,716	-,387	-,198	,223
Zscore(C14)	,711	-,103	-,153	-,310
Zscore(C5)	,669	-,316	-,335	,350
Zscore(C12)	,564	-,084	,040	,187
Zscore(C3)	,537	-,418	-,073	,346
Zscore(C13)	,440	-,224	,402	-,241
Zscore(C10)	,425	,843	-,048	,210
Zscore(C11)	,418	,832	-,015	,290
Zscore(C8)	,475	,735	-,214	,181
Zscore(C7)	,480	-,569	-,113	,220
Zscore(C2)	,049	-,061	,716	,331
Zscore(C4)	-,097	-,146	,657	,286
Zscore(C1)	,304	,138	-,108	-,399

Extraction Method: Principal Component Analysis.

a. 4 components extracted.

Factor 1 is correlated with 15 variables, Factor 2 with 7 variables, Factor 3 with 6 variables and Factor 4 with 5 variables (Absolute value of factor loading greater than 0.3). The fifth risk type is correlated with all of the four factors. Criteria 9, 12 and 17 are only correlated with one factor. The remaining 13 variables are correlated with two of the four factors. It is difficult to interpret such a complex matrix. Therefore, rotation is performed to transform the component matrix in Table 6.14 to a simpler matrix. Varimax procedure, that is the most common rotation method, is applied. The rotated component matrix is given in Table 6.15.

Table 6.15. Rotated component matrix

	Component			
	1	2	3	4
Zscore(C5)	,860	,099	,131	-,125
Zscore(C6)	,824	,261	,027	-,066
Zscore(C3)	,749	,113	-,030	,117
Zscore(C7)	,740	,131	-,222	,038
Zscore(C9)	,628	,524	,031	-,284
Zscore(C12)	,483	,284	,195	,102
Zscore(C16)	,257	,858	,246	,072
Zscore(C15)	,227	,809	,263	,094
Zscore(C17)	,310	,762	,348	,114
Zscore(C14)	,399	,609	,064	-,318
Zscore(C13)	,158	,602	-,163	,223
Zscore(C1)	-,041	,412	,087	-,322
Zscore(C11)	-,014	,125	,967	,026
Zscore(C10)	-,045	,166	,952	-,043
Zscore(C8)	,077	,148	,882	-,194
Zscore(C2)	,014	,117	,021	,783
Zscore(C4)	-,041	,018	-,115	,727

Rotation Method: Varimax with Kaiser Normalization.

*. Rotation converged in 5 iterations.

The aim of the Varimax procedure is to minimize the number of variables with high loadings on a factor. Rotation does not effect the total variance explained. However the variance explained by each factor changes by rotation. As it is seen from Table 6.15, rotation increased the interpretability of the factor matrix.

Table 6.16 is created based on the correlations in the rotated component matrix. It represents the risk variables and the extracted factors that contain these variables.

Table 6.16. Variables and factors

No.	Criteria	Factors			
		1	2	3	4
1	Previous supplier assessment score (c ₁)		x		
2	Commodity price variance (c ₂)				x
3	Financial condition of the supplier (c ₃)	x			
4	Percentage of subcontracted work (c ₄)				x
5	Manufacturing capability (c ₅)	x			
6	Flexibility (c ₆)	x			
7	Technological capability (c ₇)	x			
8	Defect rate (c ₈)			x	
9	Quality management effort (c ₉)	x			
10	Late delivery date (c ₁₀)			x	
11	Lead time variability (c ₁₁)			x	
12	Packaging and shipping quality (c ₁₂)	x			
13	Ease of communication (c ₁₃)		x		
14	Reliability (c ₁₄)		x		
15	Problem solving performance (c ₁₅)		x		
16	Warranty policy and after sales service (c ₁₆)		x		
17	Disaster recovery plans (c ₁₇)		x		

The generated four factors include six, six, three and two variables respectively. Factor 1 contains risk types related with the general structure, strength and manufacturing

capability of the supplier. Factor 2 includes risks related with the previous assessments, reliability, communication, after sales service and problem solving capability of the suppliers. Factor 3 covers the risks related with quality and delivery performance (operational performance). Factor 4 covers only two risk types; commodity price variance and percentage of subcontracted work. Companies that use subcontractors also bear the profits of these companies. This grouping of the variables is reasonable.

Table 6.17 gives the component score coefficient matrix. It represents the weights of the factors that is used to compute factors' scores.

Table 6.17. Component score coefficient matrix

	Component			
	1	2	3	4
Zscore(C1)	-,135	,214	-,058	-,227
Zscore(C2)	,025	,008	,047	,504
Zscore(C3)	,287	-,134	,022	,113
Zscore(C4)	,016	-,001	,003	,460
Zscore(C5)	,331	-,182	,076	-,025
Zscore(C6)	,273	-,080	,011	-,005
Zscore(C7)	,263	-,088	-,063	,046
Zscore(C8)	,034	-,080	,312	-,065
Zscore(C9)	,113	,108	-,057	-,172
Zscore(C10)	-,008	-,060	,340	,030
Zscore(C11)	,020	-,093	,360	,080
Zscore(C12)	,146	-,020	,066	,094
Zscore(C13)	-,081	,267	-,136	,110
Zscore(C14)	-,003	,203	-,074	-,210
Zscore(C15)	-,088	,289	-,008	,051
Zscore(C16)	-,090	,309	-,022	,035
Zscore(C17)	-,036	,231	,039	,078

Rotation Method: Varimax with Kaiser Normalization.

6.7.5. Cluster analysis

The aim of the case study is to cluster existing core suppliers of the selected company based on different risk characteristics. Totally, 72 existing suppliers were evaluated by using preprocessed risk data and 4 factors (Section 6.7.4). Clustering algorithm aims to find the similarities among suppliers based on different risk indicators. K-means clustering algorithm was applied to group suppliers based on their risk attributes. Three supplier clusters are generated with different risk exposure levels. K-means algorithm is applied with SPSS 20. Final cluster centers are given in Table 6.18.

Table 6.18. Final cluster centers

Factors	Cluster 1	Cluster 2	Cluster 3
Factor 1	-,05930	-,88048	,25743
Factor 2	-,21780	-,89619	,33325
Factor 3	-,46799	1,31841	-,13359
Factor 4	-1,23549	,10094	,53248

Figure 6.12 represents the bar chart of the final cluster centers for a better visualization.

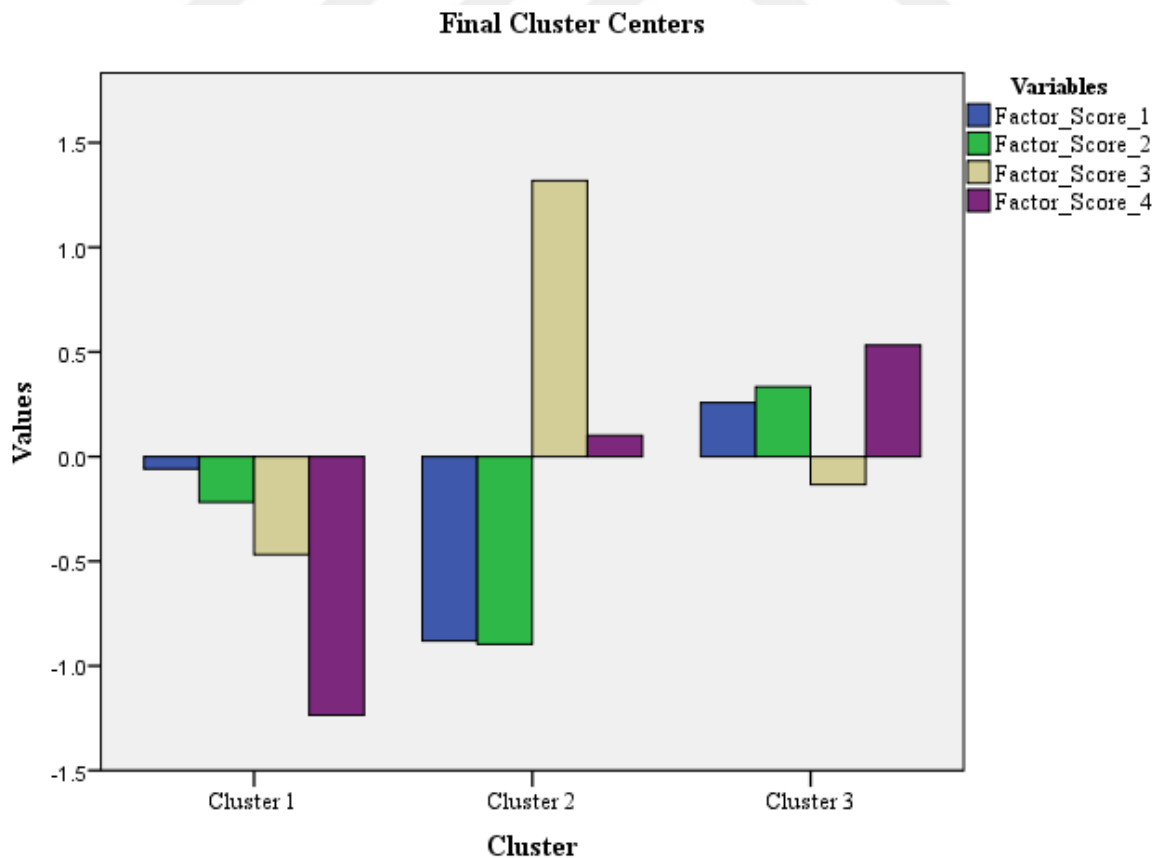


Figure 6.12. Bar chart of final cluster centers

The number and percentage of suppliers in each cluster is given in Table 6.19. More than the half of the suppliers are in cluster 3.

Table 6.19. Number and percentage of suppliers in each cluster

	Clusters	Number of suppliers in the cluster	Percentage of the number of suppliers
K-means clustering	1	19	26.39%
	2	11	15.28%
	3	42	58.33%
Valid		72	100%

Table 6.20 represents the members of each cluster.

Table 6.20. Members of clusters

Cluster 1	Cluster 2	Cluster 3		
Supplier 2	Supplier 1	Supplier 3	Supplier 37	Supplier 64
Supplier 11	Supplier 10	Supplier 4	Supplier 39	Supplier 66
Supplier 12	Supplier 17	Supplier 5	Supplier 40	Supplier 68
Supplier 13	Supplier 23	Supplier 6	Supplier 41	Supplier 69
Supplier 14	Supplier 24	Supplier 7	Supplier 42	
Supplier 15	Supplier 25	Supplier 8	Supplier 43	
Supplier 18	Supplier 28	Supplier 9	Supplier 44	
Supplier 26	Supplier 53	Supplier 16	Supplier 45	
Supplier 31	Supplier 54	Supplier 19	Supplier 46	
Supplier 32	Supplier 71	Supplier 20	Supplier 47	
Supplier 38	Supplier 72	Supplier 21	Supplier 50	
Supplier 48		Supplier 22	Supplier 55	
Supplier 49		Supplier 27	Supplier 56	
Supplier 51		Supplier 29	Supplier 57	
Supplier 52		Supplier 30	Supplier 58	
Supplier 62		Supplier 33	Supplier 59	
Supplier 65		Supplier 34	Supplier 60	
Supplier 67		Supplier 35	Supplier 61	
Supplier 70		Supplier 36	Supplier 63	

An ANOVA test is applied to examine if there are significant differences between risk factors in different clusters. The ANOVA table for the cluster analysis is given in Table 6.21. As it is seen from the table, the four factors have a significant effect on clusters.

Table 6.21. ANOVA table for k-means clustering

	Cluster		Error		F	Sig.
	Mean Square	df	Mean Square	df		
Factor_score_1	5,689	2	,864	69	6,584	,002
Factor_score_2	7,200	2	,820	69	8,778	,000
Factor_score_3	12,016	2	,681	69	17,652	,000
Factor_score_4	20,511	2	,434	69	47,212	,000

6.7.6. Results and Discussion

The raw supplier risk data is normalized and a factor analysis is applied in order to reduce the number of variables. 17 risk types are reduced to four factors after performing a PCA. Then 72 suppliers are clustered into 3 clusters by using the k-means clustering algorithm. The spider web diagram in Figure 6.13 compares the final cluster centers for the four factors.

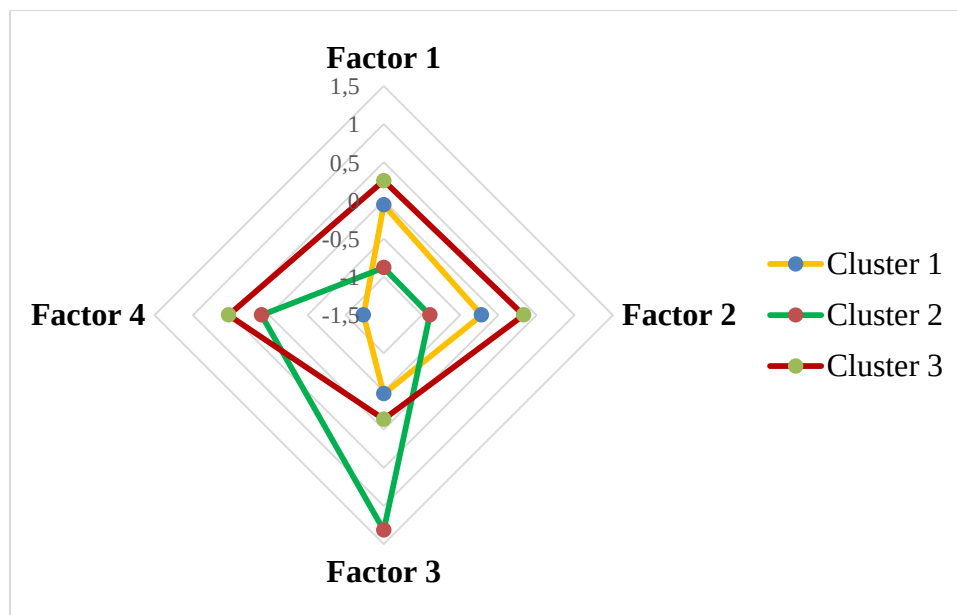


Figure 6.13. Spider web diagram of the cluster centers for the four factors

Factor 1 contains risk types related with the general structure, strength and manufacturing capability of the supplier. Factor 2 includes risks related with the previous assessments, reliability, communication, after sales service and problem solving capability of the suppliers. Factor 3 covers the risks related with quality and delivery performance (operational performance). Factor 4 covers only two risk types; commodity price variance and percentage of subcontracted work. Companies that use subcontractors also bear the profits of these companies. If we compare the final cluster centers for factor 1 and 2, we see that cluster 3 has the highest risk level and cluster 2 has the lowest risk level. Clusters 1 and 3 have the same order based on factor 3, but the risk level of cluster 2 changes from the lowest to the biggest for this factor. It means that the suppliers in cluster 2 have a low risk level related with their managerial, manufacturing, problem solving capability and relational performance. However, these companies have a low operational performance in terms of quality and delivery performance. Based on factor 4, commodity price variance and percentage of subcontracted work, the highest risk profile belongs to cluster 3 and the lowest risk level is observed in cluster 1. Cluster 3 has a higher risk level based on the three factors. Based on the evaluation of the clusters for the four factors, we can conclude that the suppliers in cluster 3 has the highest risk profile. We need to consider the supplier evaluations for the 17 risk factors and the weights of the risk criteria to reach a conclusion for supplier clusters 1 and 2.

The raw data should be examined in order to understand the risk structure of each supplier cluster and a more accurate interpretation of the results. Table 6.22 represents the mean of the 17 risk criteria for the three clusters. Dark grey cells show the highest mean values for the risk types. Medium grey cells represent medium scores and light grey cells represent the lowest risk scores. Cluster 3 has the highest risk scores for most of the risk types. This supplier cluster can be labeled as “suppliers with a high risk level”. These results are compatible with the spider web diagram of the cluster centers for the four factors (See Figure 6.13). Cluster 2 has the lowest scores for most of the risk types related with the manufacturing capability and operational performance (e.g. flexibility, technological capability, packaging and shipping quality, problem solving performance, warranty policy and after sales service). Cluster 2 can be labeled as “suppliers with a low risk level”. However, the suppliers in this cluster has a highest

level of defect rate and delivery lateness. The commodity price variance and percentage of subcontracted work criteria have high values for these suppliers too. In addition, although suppliers in cluster 2 have a high level of commitment to quality management efforts, the quality problems resulting from their subcontractors effect their performance.

The suppliers in cluster 1 has average risk scores for most of the risk types. Cluster 1 can be labeled as “suppliers with a medium risk level”. However, they have the lowest risk levels for the following five risks: commodity price variance, percentage of subcontracted work, defect rate, late delivery date, and lead time variability.

Table 6.22. Means of the seventeen risk types for the three supplier clusters

	Cluster 1	Cluster 2	Cluster 3
Previous supplier assessment score (c1)	2.39	2.09	2.29
Commodity price variance (c2)	4.63	6.82	7.31
Financial condition of the supplier (c3)	4.54	3.91	4.91
Percentage of subcontracted work (c4)	0.13	0.34	0.54
Manufacturing capability (c5)	4.93	4.16	5.13
Flexibility (c6)	4.84	4.27	5.07
Technological capability (c7)	4.85	4.12	5.20
Defect rate (c8)	0.12	0.26	0.13
Quality management effort (c9)	4.93	3.51	4.83
Late delivery date (c10)	0.11	0.32	0.15
Lead time variability (c11)	0.10	0.35	0.17
Packaging and shipping quality (c12)	5.38	4.91	5.92
Ease of communication (c13)	3.95	3.21	4.62
Reliability (c14)	4.79	3.64	4.80
Problem solving performance (c15)	4.54	4.33	5.43
Warranty policy and after sales service (c16)	4.52	4.35	5.45
Disaster recovery plans (c17)	4.44	4.36	5.35



The results of the analysis are interpreted with the domain experts. They stated that most of the suppliers in Cluster 1 and Cluster 3 sell simple products that provide the opportunity to hold stock. In addition, most of the suppliers in Cluster 2 produce complex products. These issues explain the different cluster profiles for defect rate, late

delivery date and lead time variability. A product complexity variable may be added to the analysis.

Cluster profiles differ for the previous supplier assessment scores too. The company implements supplier development plans if a supplier took bad scores for a performance factor. Therefore, previous supplier assessment scores may be collected before an improvement has been applied.

The company may prefer to work with the suppliers in Cluster 2, or they may consider the weights of the risk criteria that are identified in Section 6.7.3. The selection of the most desirable supplier cluster may depend on these weights. As an example, commodity price variance was determined as the most important risk criteria. The company may choose one of these clusters by considering the importance of the criteria. As a third approach, the company may create supplier development programs to improve the risky areas in the supplier clusters.

This study makes four contributions to the literature:

- It develops a supplier evaluation framework with a SC risk perspective. Selected supply risk factors are used as supplier evaluation criteria.
- Suppliers are clustered according to their risk profile. To our knowledge, this is the first study that clusters suppliers according to their risk profile.
- Besides traditional supplier evaluation issues, sustainability related issues are considered in evaluating suppliers (e.g. disaster recovery plans).
- The clustering based framework to evaluate suppliers based on their risk profile is verified with a real-life case study.

Despite the contributions, this study has several limitations. It was hard to define and convert some of the risks (especially social and environmental) into measurable variables. Supplier evaluation and selection process requires information about potential suppliers such as past performance, financial status of the supplier, quality management programs (Wu, 2009). The availability, accessibility, consistency and accuracy of the supplier related data generally constitutes a problem.

7. CONCLUSION

In the recent decade, companies have to pay attention to the threats and risks as well as opportunities in order to develop policies and state strategies for global competitiveness. Therefore, effective risk actions started to gain a critical importance in the context of SCM. There are a variety of articles (in forums, consultancy firms' web pages, etc.) and business reports about risks and their sources. Various business trends and developments rise the risk exposure levels of SCs and make companies vulnerable to unforeseen disruptions. Companies have to deal with huge amounts of different and distributed data sources in order to take right decisions and handle with the risks in SCs (Marra et al., 2012; Lam and Quinn, 2014). Scope and volume of the SC data are growing with increased globalization, collaboration, communication and the developments in information technologies. Terabytes of data are generated and transmitted in everyday operations in many SCs; e.g. production records, billing records, delivery records, surveys, etc.

Decision making is getting harder every day due to increasing uncertainty, complexity, high velocity and volume of data streams, agility, dynamism and competitiveness in the global business environment. There is a need for new and effective approaches to cope with the increasing risk exposure levels and manage growing information load. Today a lot of companies use BI tools and techniques in SCM to make efficient and timely decisions (Manhattan Associates, 2008). In addition, the number of companies that use BI tools to support SCRM process is increasing. Companies save billions of dollars by using BI solutions for their daily operations. However, the academic literature is not rich enough on the use of BI and DM tools and techniques in SCRM, and there is a research gap for the relationship between these two areas (Petrini and Pozzebon, 2009; Lee and Kulkarni, 2011; Wu et al., 2014). There are only a few studies in the literature related with the application of DM algorithms in SCRM (Thun and Hoenig, 2011; Ye et al., 2012; Le et al., 2013). This field is new and promising for providing effective risk management systems. Hence, we expanded the scope of the literature review to cover BI area and the use of BI tools and techniques in managing SCs and their risks.

The key success factor to develop a responsive and adaptive SCRM is the effective analysis of the risk related data. Scope and volume of the SC data are growing with the

increasing complexity of the SC networks and advances in technological developments. However, data means nothing without bringing it to a meaningful knowledge. There is a need for researches on how to systematically analyze risk related data to discover and assess risks (He and Song, 2009). The motivation behind the study is the lack of a framework to apply DM tools and techniques for SCRM in the academic literature. Therefore, this thesis aims to contribute this research gap by proposing a DM-based SCRM model in order to make more informed and intelligent decisions in risk management.

Two different research fields are integrated to develop the proposed model: SCRM and BI. Therefore the scope of the literature review is divided into four main parts under these two main areas i) SC risks, ii) main steps and approaches in SCRM, iii) BI and DM, and iv) the applications of BI and DM tools in SCRM. The literature review provides the background information for the incorporation of SCRM and DM areas. The first part focuses on SC risks and oft-cited risk events in order to understand risks and the origins of SCRM. A comprehensive review on SC risks is given and a new categorization is proposed for SC risks. Secondly, some of the methods and strategies are given for mitigating SC risks. The relationship between sustainability and SCRM concepts is introduced briefly with a multidimensional approach. Finally, a literature review is presented on the researches associated with data analysis and management both in SCM and SCRM fields. Then some risk related data and indicators that are used by enterprises are explained briefly.

DM covers the tools and techniques that are used to uncover hidden, previously unknown and useful information about risks from the databases of the company. DM provides the opportunity to analyze risky points in the SC processes and the underlying reasons for these risks. DM helps companies to discover risks and opportunities easily and improves the visibility of the risks. DM can be used in the discovery, assessment, analysis, prediction, monitoring and prevention of the risks in SC networks. DM tools and algorithms have the potential to bring analytical insights to the SCRM area. The proposed model helps to transform risk data to risk knowledge. There is a lack of academic researches that study on the usage and impact of data management practices in SCRM. The role of DM in risk management at the SC level needs a deeper understanding.

The primary goal of this thesis is to develop a DM-based SCRM model in order to increase the effectiveness of risk management decisions by utilizing the results of DM algorithms. The main steps of DM and Risk Management are combined by adding a DM module to the SCRM framework. DM module provides real time and useful information about selected risk factors by analyzing the risk-related internal and external SC data. This general model provides a systematic way of using DM tools and techniques in SCRM. To the best of our knowledge, this study is novel in the SCRM area. In this model, DM is used to extract useful information about risks for identifying effective risk management actions. The proposed framework provides a comprehensive guide to build and implement the SCRM framework supported by DM tools and techniques. Raw data about risks is extracted from various internal and external databases and loaded to the RDW. A risk data mart is created from this data warehouse for the current DM analysis. Risk data mart (risk problem database) is a subset of the RDW and created from the data warehouse by transforming, summarizing and shaping the data according to the requirements of the DM application. Risk data is gathered from the server by the DM module. The DM-based architecture is used to convert risk data to risk information and knowledge. Risk wisdom is also addressed as an extension to this framework. Risk wisdom is created by embedding the experience, beliefs, perspectives and understanding of the experts to the risk knowledge.

This thesis focus on building a general model rather than specifying each technique of DM. The lens approach used in Amundson (1998) and Done (2011) is adapted to represent the role of SCRM and DM fields in the development of the DM-based SCRM model. A lens is directed towards the objective of the development of an effective DM-based SCRM model. The studied model changes with the developments in the SCRM and DM areas and, the technological innovations. The lens can only capture the environment that is within the sight of the observer (Amundson, 1998). The objective also varies based on the characteristics of the observer and the lens. Therefore, the development of a DM-based SCRM is dependent on the structure of the sector, SC network and risk attitude of SC executives. The implementation issues, advantages and limitations of the proposed model are discussed in detail.

Types, severity and frequency of risks vary according to the industry, business and the structure of the company. In addition, each company has its own risk profile, risk

attitude and risks. Therefore, the application part of the study concentrated on one specific company. The proposed DM-based SCRM model is partially adapted to the selected company in order to explain and detail the application of the model. The steps of the proposed model are applied respectively. First a risk analysis and management team is created that contains risk experts, domain experts and a data analysis expert. The risks that the company is exposed to are identified and explained with discussions, brainstorming and focus group studies. A risk evaluation form is applied in the company in order to assess some of the most important risk factors. Then, the risk indicators that can be used to measure and track these risks are identified with discussions and literature review. The development of a data warehouse and the proposed DM based risk management framework is a long term project. Therefore, only risk indicators are determined in order to provide an initial basis of a RDW for the company. In addition, potential DM applications are listed. The results of the performed studies will be used to embed the proposed DM-based SCRM structure into the company's new information management system.

An industrial case study is implemented to illustrate the applicability of the DM-based SCRM model. The aim of the case study is to represent the applicability and advantages of the DM-based SCRM model with a real case study. Supplier risk is selected as a risk problem and cluster analysis is applied as a solution method to mitigate this type of risk. Seventy-two core suppliers of the company are evaluated based on seventeen qualitative and quantitative risk criteria. Tangible and qualitative supplier evaluation criteria are also used in order to cover various dimensions of SC risks (e.g. reliability, disaster recovery plans). Risk evaluation criteria are assessed by three decision makers via using the BWM which is a new MCDM method (Rezaei, 2015). Then, four factors are extracted from these seventeen criteria by applying PCA. K-means clustering algorithm is applied to group suppliers and three different clusters are created with different risk levels. Based on the evaluation of the clusters for the four factors, we can conclude that the suppliers in cluster 3 has the highest risk profile. We need to consider the supplier evaluations for the 17 risk factors and the weights of the risk criteria to reach a conclusion for supplier clusters 1 and 2. The raw data is examined in order to understand the risk structure of each supplier cluster and reach a more accurate interpretation of the results. The mean of the 17 risk criteria for the three clusters are

calculated and evaluated. Cluster 3 has the highest risk scores for most of the risk types. This supplier cluster can be labeled as “suppliers with a high risk level”. Cluster 2 has the lowest scores for most of the risk types related with the manufacturing capability and operational performance, therefore it can be labeled as “suppliers with a low risk level”. The suppliers in cluster 1 has average risk scores for most of the risk types, hence Cluster 1 can be labeled as “suppliers with a medium risk level”. The company may prefer to work the suppliers in Cluster 2, or they may consider the weights of the risk criteria to make a decision. As a third approach, the company may create supplier development programs to improve the risky areas in the supplier clusters.

This study is novel based on two dimensions: i) application of cluster analysis to group suppliers based on their risk profile, and ii) application of BWM and cluster analysis in the same model. The results of the cluster analysis are interpreted to identify risk management actions. Supply risks will be decreased with the consideration of supplier related risk factors in evaluating suppliers. The interpretation of the DM results provides insights for risk management actions to mitigate supplier risk. Suppliers with a high-risk profile can be eliminated or supplier development programs can be developed based on the results of the analysis. The aim of the case study is to represent the applicability and advantages of the DM-based SCRM model with a real industrial study.

This thesis will provide an initial basis for further researches and developments in the application of DM algorithms in SCRM. The proposed DM structure will support and enhance the SCRM processes (such as risk identification, risk assessment, risk management actions and risk monitoring), support SC intelligence and help companies to survive and compete within today’s complex and dynamic environment. DM-based SCRM contributes to the survival and sustainability of organizations by providing the opportunity to extract knowledge from risk data. The results gained by the DM algorithms will provide a realistic picture of the state of the SC risks for decision makers seeking to manage risks in SCs. The main contributions of the thesis can be summarized as follows: i) development of a general DM-based SCRM model, ii) clustering suppliers considering supply risk, and iii) application of an industrial case study.

Several promising directions can be done for future research both for the DM-based SCRM model and the clustering application. First, the proposed DM-based SCRM

framework will be incorporated into the new information system of the company. The company is negotiating with software companies for the development of a new enterprise information system. The results of the performed studies and the proposed risk management structure will be used in a further study to embed the proposed DM-based SCRM structure into the company's new information management system. An expert system may be developed for the selection of DM applications. In addition, the increases in the variety, scope, scale and volume of data generated by SC operations drive companies to use big data concept in SCM and SCRM. Organizations started to mention from big data era instead of data. Therefore big data analytics may be incorporated to the proposed SCRM model.

For the case study, different clustering algorithms can be applied on the supplier risk data. These alternative techniques may be compared based on the number of clusters, performance and accuracy.

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APPENDIX A

RISK EVALUATION FORM

The aim of this questionnaire is to identify the most critical risks for your company and list them based on their importance level. Your risk ratings will be used in the identification of risk prevention and management activities.

Information about the respondent:	
Department:	Experience in this company(year):
Education level:	Total experience (year):
Job title:	

Please grade the following risk according to its frequency, severity of its consequences and difficulty of detectability according to the given risk scale tables.

	Risk Level			Risk Priority Number
	Frequency	Severity	Detectability	
Sales and Marketing Risks				
Customer dissatisfaction				
Failure products / projects				
Low performance of sales team				
Low service levels				
Contractual risks				
Customer Risks				
Customer payment problems				
Design Risk				
Mismatch of customer expectations				
Long design cycle time				
Wrong feasibility studies				
Low product / process standardization				
Human error				
Frequent design changes				
Purchasing / Supply Risks				
Supplier quality problems				
Supply delivery problems				
Inadequate supplier management				
Poor supply planning				
High level dependence on suppliers				
Bankruptcy of supplier				
International business risk				

	Risk Level			Risk Priority Number
	Frequency	Severity	Detectability	
Manufacturing Risks				
Capacity problems (uncertain capacity, low capacity utilization, etc.)				
Poor operational performance				
Quality problems				
Breakdown of equipment / machinery				
Occupational accidents				
Poor performance measurement and management system				
Poor manufacturing planning and scheduling				
Logistics Risks				
Late deliveries				
Incompliance to shipping instructions				
Poor packaging				
Financial Risks				
Delayed payments from customers				
Cash flow risk				
Volatile exchange rate				
Volatile prices				
Human Resources Risk				
Low employee satisfaction and demotivation				
Poor working conditions				
Loss of a key staff				
Unavailability of qualified labour				
Information System Risks				
Ineffective Information System				
Failures of Information Technologies and Systems				
If you want to add another risks, please write below:				
1)				
2)				
3)				

Please grade the following functions of the company from 1 to 10 based on their risk exposure level. (1: low risk level, 10: high risk level)	
Sales	
Marketing	
Product/Project Design	
Manufacturing	
Production Planning	
Purchasing	
Packaging and Shipment	
After Sales Service	

Rating for the frequency of the risk factor
(DrugRegulations, 2015)

Level	Effect
10	More than once a day
9	3-4 times a day
8	Once a week
7	Once a month
6	Once in three months
5	Once in half-one year
4	Once a year
3	Once in 1-3 years
2	Once in 3-5 years
1	Less than once in 5 years

Rating for the severity of the risk factor
(Selvan et al., 2013)

Level	Effect
10	Hazardous without warning
9	Hazardous with warning
8	Very high
7	High
6	Moderate
5	Low
4	Very low
3	Minor
2	Very minor
1	None

Rating for the detectability of the risk factor
(Selvan et al., 2013)

Level	Effect
10	No chance of detection
9	Very remote chance of detection
8	Remote chance of detection
7	Very low chance of detection
6	Low chance of detection
5	Moderate chance of detection
4	Moderately high chance of detection
3	High chance of detection
2	Very high chance of detection
1	Almost certain detection

BIOGRAPHY

Merve ER KARA was born in 1986 in İstanbul. She is a research assistant and a PhD student in department of Industrial Engineering at Marmara University, Turkey. She graduated from Industrial Engineering Department at Sakarya University in 2008. Then, she had her master degree from Industrial Engineering Department at Marmara University in 2010. Her research interests are Supply Chain Risk Management, Sustainability, Data Mining and Metaheuristics.

