RESILIENT SUPPLIERS SELECTION SYSTEM USING MACHINE LEARNING ALGORITHMS AND RISK ASSESSMENT METHODOLOGY

by

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To my father, mother, siblings, wife, and child

for their support....

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ABSTRACT

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Demand, supply, pricing, and lead time are all unpredictable in the manufacturing industry, and the manufacturer must function in this environment. Because of the enormous amount of data available and the introduction of new technologies, such as the internet of things (IoT), machine learning (ML), and Blockchain, administrators and government officials are better able to deal with uncertainty by applying intelligent decision-making principles to their situations. All supply chains must make use of new technology and analyze previous data to forecast and improve the success of future operations. At the moment, we rely on the supply chain and its facilities for healthcare when we receive our vaccine, for our food when we go grocery shopping, and for transportation when we drive our cars. Supplier selection is exposed to the three most significant factors: quality, delivery, and performance history, which are all evaluated separately. The use of data analytic capabilities in the selection of robust supplier portfolios has not been thoroughly investigated. Manufacturers typically have three to four resilient suppliers for the same item, but occasionally one or two of them will fail, causing a ripple effect throughout the entire supply chain. This is a frequent problem that the supply chain must deal with on a daily basis. Supply chain resilience, on the other hand, ignores or is incompatible with the risk profiles of suppliers' performance.

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IoT	The Internet of Things
ML	Machine Learning

CHAPTER ONE

INTRODUCTION

This chapter presents an overview of supply chain management and a resilient supplier selection framework in order to provide a thorough account of the proposed activity. Additionally, the techniques that were used to create this work are described.

1.1 Introduction

A supply chain management (SCM) is a chain of facilities that purchases raw materials, transforms them into finished consumer products, and then distributes them to consumers through a distribution system [71]. Supply chain management's primary activities are inbound logistics, operation (manufacturing), outbound logistics, marketing, and services, as shown in Figure 1.2. Inbound logistics is the first supply chain activity, where suitable raw materials or products from the right suppliers are received at the correct warehouse, or are directed to the right factory [66]. Inbound logistics include supplier selection, and the procurement and receipt of raw material or primary product. The second activity on the supply chain is the operation or manufacturing process of producing products using labor, machinery, and tools. Manufacturing involves designing, assembly, and material inspection. Outbound logistics represents the process required to deliver the final product to the end user [121]. The third activity in the supply chain is entitled product processing, packaging, transportation and delivery of the final product. The fourth step on the supply chains' activities is marketing, which is the process of conceptualizing, pricing, promoting, and distributing concepts, goods, and services to facilitate transactions that benefit both individuals and organizations [88]. The last supply chain activity is any intangible operation or benefit provided by one party to another, including activities involved in the services, installation, integration, monitoring, and optimization of the product.

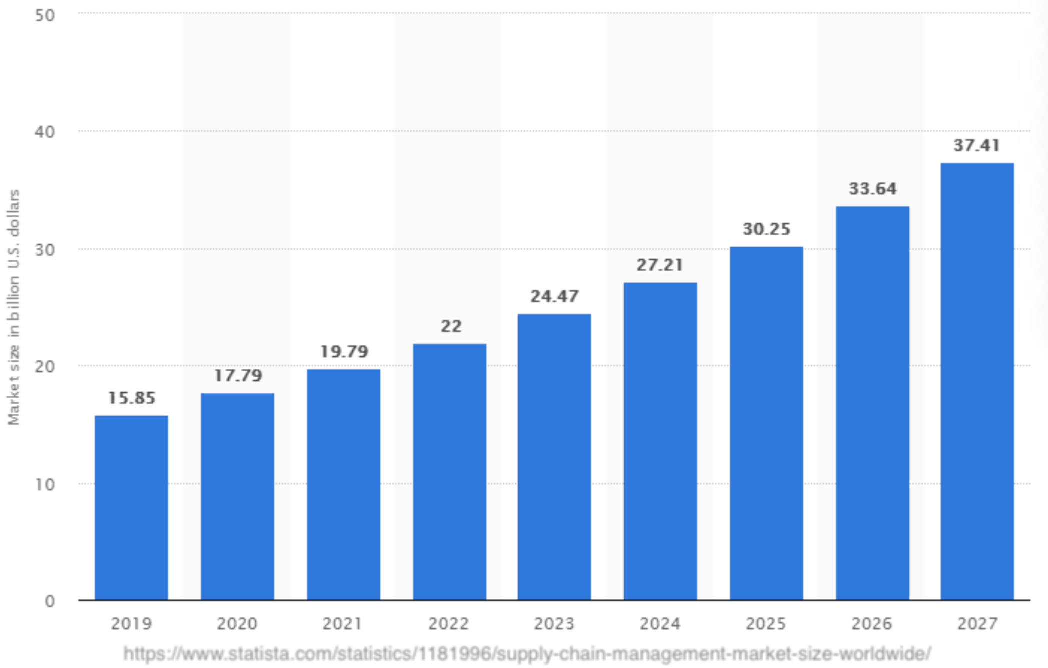

Figure 1.1: Growth In The Size of Supply Chain

The idea is to connect the main activities of SC to promote a robust and resilient SC network. Several concepts contribute to this idea's advantage, including minimizing stock-out costs in addition to monitoring and controlling all costs of storing, transporting, and purchasing [129].

In 2019, statistics showed that the growth of the global supply chain management size was expected to reach 37.4 billion dollars in 2027, more than doubling from 15.85 billion dollars in 2019. See Figure 1.1. The global supply chain management market is growing as a result of the advancement of industrial-grade digital technology, a rise in demand for better supply chain visibility, and a growing preference for cloud-based supply chain management software. Additionally, there has been an increase in supply for

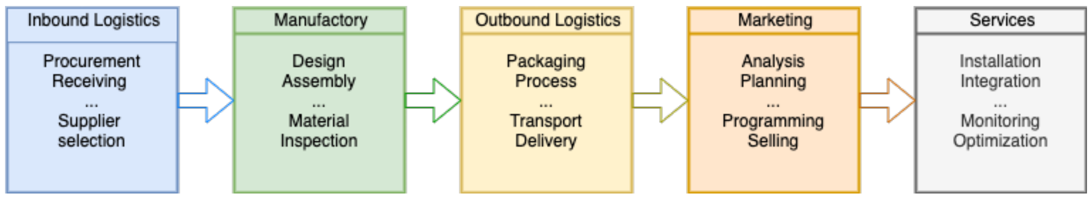

Figure 1.2: Supply Chain Activities

demand management solutions among businesses and an increase in the adoption of SCM software. However, the high cost of deployment and maintenance of SCM solutions, as well as an increase in corporate security and privacy issues, are expected to restrain market growth. On the other hand, an increased demand for transportation management systems (TMS) software and the introduction of internet of things (IoT), big data, blockchain, and machine learning technology into supply chain management (SCM) software are expected to create significant market expansion opportunities in the near futur [29]. The new key market segment, which is predominantly comprised of small and medium enterprises (SMEs) and large enterprises, is focused on solutions, services, and user types. Solution types include sourcing and supplier selection systems, supply chain planning systems, and manufacturing execution systems.

The enormous amount of partnerships results in lower purchasing costs for the supply chain's core members. Once the supplier has more comprehensive information on demand, all will handle their operations more effectively [129]. The manufacturer operates in an area of uncertainty in demand, supply, cost, and lead time. The tremendous amount of data available and new technology, such as internet of things (IoT), machine learning (ML), and blockchain, empowers administrators and government officials to deal with uncertainty through the application of intelligent decision-making principles [21]. All supply chains need to enable the new technologies and use historical data to predict

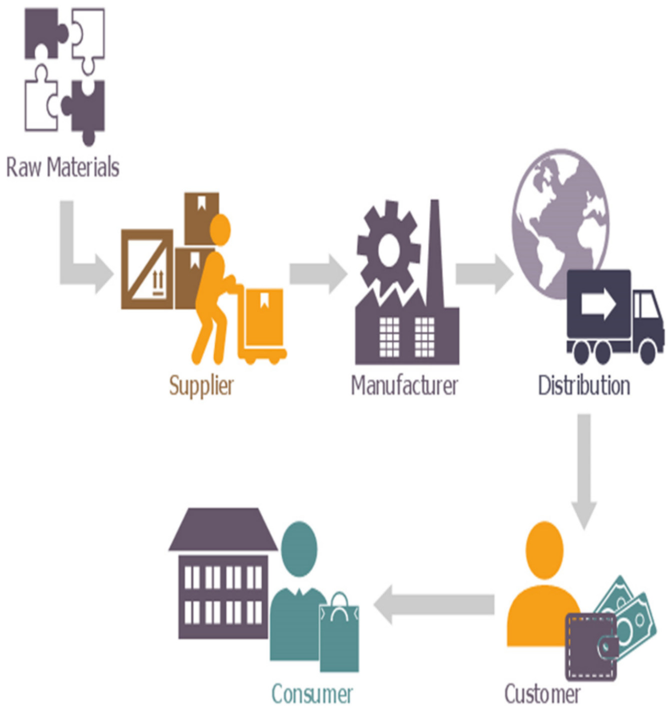

Figure 1.3: Supply Chain system

and enhance future processes. Most research shows there is no room for manual processes with the tremendous rise in demand. Nowadays, we rely on the supply chain and its facilities for our health when we receive vaccines, on our food when shopping for our meals, and on our commute when we ride in our cars.

Supply chain managers aim to achieve completely integrated supply chain systems, where efficient and effective supply chains are capable of establishing and maintaining competitive advantages [26]. This entails balancing downward cost pressures and the desire for efficiency with means of managing the demands of market-driven service requirements, as well as the known risks of routine supply chain breakdowns, to achieve their objectives [62]. Improved management and control of internal processes, as well as more transparent information flows within and across organizations, may go a long way toward addressing this issue [13].

Supply networks are becoming more volatile and unpredictable, which is driving traditional supply chain management strategies to become ineffective. The potential of natural disasters, sociopolitical upheaval, conflict, economic uncertainty, and market volatility, among other things, constantly threaten catastrophic disruption [52]. What methods do we use to detect and prioritize such risks? Many industries have struggled to keep up with the rising complexity of logistics, resulting in a supply chain that is less resilient than it should be. The majority of supply chain managers have done nothing to address this issue. The development of contingency rules and procedures for operations during a complicated, high-risk event is beyond the capabilities of many large corporations. A majority of the managers interviewed either do not actively work on supply chain risk management or do not believe their company's risk management strategies are successful in their current position of authority [53].

To uncover and adjust to constantly evolving risks, overcome disruptions to its primary earnings drivers, and create advantages over less adaptive competitors, a resilient and robust supply network links and aligns its strategy, operations, management systems, governance structure, and decision-support capabilities in an efficient and effective manner. Furthermore, it possesses the aptitude and ability to adapt promptly to unanticipated events, including interruptions caused by unforeseen circumstances. Supply networks' resilience is defined as their capacity to foresee and recover from failures via the use of standardized processes, speed, determination, skilled supply management, and precision [36].

A supply network's strategy and operations should be aligned to adjust to the risks that impact its capacity. In the supply chain, there are four steps of resilience. First is reactive supply chain management; second is internal supply chain integration with planned buffers is the second step; then follows the merging of supply chain networks around the world; and finally, supply chain agility and adaptability is the fourth step[37].

The resiliency of supply chain systems should be achieved at the strategic and operational level. Strategic resilience focuses on long-term supply risk prevention through standardized and advanced supply management. As the supply environment changes, a supply network must constantly reinvent business models and tactics. It is not only about a quick fix or a flexible supply chain[36]. Rather, resilience requires the anticipation of and adjustment to persistent discontinuities to reduce the value of a core business by focusing on delivering ultimate customer focus. Thus, strategic resilience necessitates product structure, process, and corporate behavior. Renewal is a natural outcome of a supply chain strategic resilience. Moreover, supply managers must operate as risk managers [52]

In the context of operational resilience, supply networks are more concerned with operational concerns than strategy or tactics [53] Because of this, they must respond to the organization's daily requirements and promptly adapt to those expectations [36]. The operational resilience of an organization must take into account short-term measures in terms of product-service mix, processes, and supply chain, by increasing the agility, robustness, and flexibility of the organization in the face of changing circumstances [105]

Accordingly, it is necessary to develop new system models between original equipment manufacturers (OEMs) and suppliers in a collaborative project manner. Suppliers supply the noncore competence product range, allowing companies to specialize and concentrate on their core skills and those of their strategic partners [52]. Another necessity is standardized supplier integration within the OEM by systematizing the assessment of each supplier in a dynamic using machine learning (ML) techniques, which include the continuous and cross-functional review of suppliers' performance data which is obtained from its risk profile to define and execute actions as quickly and efficiently as possible to maximize efficiency. The identification and mitigation of present and

Table 1.1 Supply chain system resiliency requirement

Resiliency Propriety	Definition
Connectivity	Information systems connectivity and physical connectivity are the two variables that enable the supply chain to run seamlessly.
Availability	The percentage of products that are available at any given time.
Redundancy	Ensure that the supply chain is not harmed in any way. Prevent slowdowns or, even worse, shutdowns.
Efficiency	The most optimum use of supply chain resources including financial, human, technological or physical
Collaboration	Two or more autonomous firms working jointly to plan and execute supply chain operations

foreseeable hazards must take place throughout the whole supply chain to specify preventative actions. The supplier risk management outcomes can provide efficient coordination of the supplier base in its behavior and assessment.

1.2 Problem Statement

The challenge for businesses today is to manage and minimize risk by establishing more resilient supply chains, which is a challenging task. Many manufacturers have growing issues with supplier selection. Supplier selection is a critical issue for keeping competitive advantages in supply chain management (SCM). Supply chain management's primary activities are inbound logistics, operation (manufacturing), outbound logistics, marketing, and services. Precise and consistent features of non-failure, long-lasting service, and flexibility are the main characteristics of supply chain resilience. Accomplishing supply chain resilience means taking both reactive and constructive

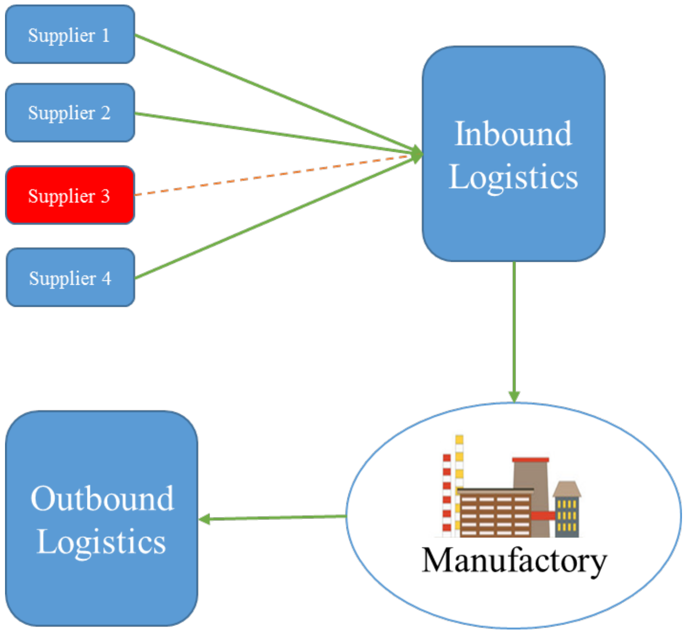

Figure 1.4: Disruptive Supplier Affect

approaches, such as developing unique precautions and preparing for future disturbances by contingency plans or backup supply planning. According to several studies, supply chain agility and supply chain resilience are dynamic qualities that have a tremendous impact on efficiency.

Finding qualified suppliers with whom one can build long-term, mutually beneficial partnerships is a difficult strategic challenge. We focus on this study on the resilient of supplier selection which is supportive activity for the supply chain resiliency. The ability of a system to recover its original condition or migrate to a new, more desired state after being disturbed is what we mean by "resilience"[52]. The resilience of supplier selection is subject to important factors such a: cost, time of delivery, and delivery method, as shown in 1.5 below. The distance from supplier to manufacturer matters when there are global disruptions, such as the ongoing COVID-19 pandemic. Learning from this major

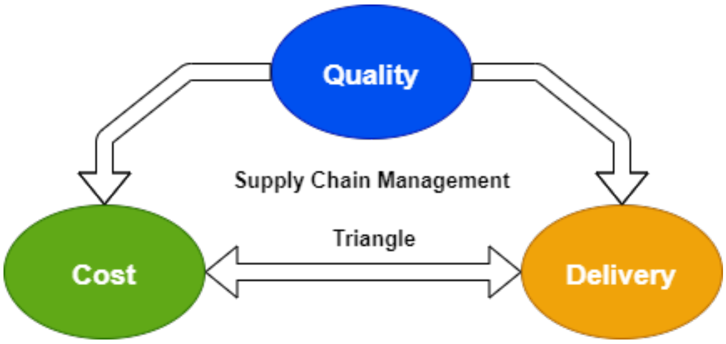

Figure 1.5: Supply Chain Triangle

disruption, many countries worked on solutions like ally-shoring. Other factors may make a supplier preferable based on the quality of the goods and the means of delivery. The data analytic capabilities in selecting resilient supplier portfolios have not been formally examined. Most suppliers work on make-to-order style and on-time-delivery (OTD) methods and these are considered features of a resilient supplier. SME's manufacturers usually have three to four suppliers for the same item, but sometimes one or two of them drop down which impacts the entire supply chain. This is a common issue supply chains regularly face. Previous studies have focused on obtaining alternative suppliers and finding quick fixes for this issue; however, this leads to supplier's risk profiles being ignored or suppliers being deemed compatible with supply chain resilience. Our finding objective is to mitigate two causes found as a problem statement. First, the resiliency level of suppliers is neglected. Second, the risk level of suppliers is ignored by SME manufacturers.

1.3 Research Questions

This work aims to develop and build a risk profile for each supplier in the supply chain system to promote a more capable and resilient supply chain that can withstand unforeseen disturbance. The question is how to use machine learning techniques to build such a system model that accurately represents supplier selection systems and design it dynamic enough to resist any challenges that could negatively affect the whole supply chain system.

- Has the examined supply chain system been delayed in the near past?
- How can we ensure the data of the supply chain system is accurate?
- What is the important feature that the supplier selection system should consider?
- What are the preferred delivery methods for the manufacturers?
- What makes a supplier resilient or non-resilient based on the historical data layer?
- How successful are machine learning techniques to determine resilient suppliers from non-resilient suppliers?
- How can we build a risk profile for each supplier in the second layer of the system?
- How well does the system model adapt upon exposure to various test settings?
- How can the system perform the behavior of a supplier?

1.4 Research Objectives

Due to a massive number of disruptive events in the past, many purchasing corporations have seen their operations suffer due to the scarcity of raw materials [41]. For example, Philips experienced a fire at their New Mexico microchip plant which resulted in the stoppage of the facility's output. Naturally, this had a severe impact on the operations of its customers. Ericsson, one of Philips' buyers, suffered a revenue loss of approximately 400 million dollars as a result of this event [95]. Furthermore, the earthquake and tsunami that struck Japan in 2011 had a significant impact on Apple's supply chain since a number of its suppliers were forced to close their doors due to the natural disaster. For a period of time, this resulted in delays in the availability of components for the iPad2 [123].

Currently, the COVID-19 outbreak is causing significant disruptions in supply chains and manufacturing operations throughout the world. It is predicted that thousands of assembly plants in the United States and Europe will be forced to close for an extended period of time due to their reliance on Chinese suppliers [120].

Supplier resilience is becoming increasingly important to industrial organizations due to the increased acknowledgment of the importance of supply chain continuity [57]. he goal of this research is to address the limitations and challenges of supplier selection by proposing a system model that examines all suppliers, and building a risk profile for each supplier using machine learning techniques.

The method to increase the resiliency and adaptability for the entire supply chain system is to investigate each supplier and build a risk profile based on its historical data. Based on these data, predictive modeling is applied to identify resilient suppliers from non-resilient companies that create disruptive changes in the supply chain system. We propose a system named resilient suppliers selection system (RSSS) that is comprised of two layers: historical data and a risk profile for each individual supplier. As part of the training step, we developed a classifier model, then we predicted the model based on accuracy, and we concluded this layer with a clear decision as to whether a supplier is resilient or not. The second layer is the development of a risk profile for each supplier; this step will be carried out using a statistical approach and will be updated in response to supplier behavior. After that, the report will be forwarded to the manufacturing log. As an added bonus, following this layer, we updated the historical data for each of the suppliers. Our proposed resilient suppliers selection system (RSSS) will have the following objectives:

- Develop an automated and lightweight solution that examines all suppliers and detect if they are resilient or not.

- Building risk profile for each supplier.
- Study, train, and predict supplier behavior over time.
- Reduce the disturbance for suppliers by making the system understand them.
- Decision makers can clearly decide when the visibility is high on each supplier, whether they continue with/or discontinue or invest in them to improve.
- The whole supply chain will be more resilient and capable.
- Manufacturers will improve their reliance on their suppliers.
- Reporting the manufacturer and restoring in a database the analyzed suppliers.
- Suppliers' weaknesses and strengths are present in the supplier report.

1.5 Organization of Dissertation

The remainder of this dissertation is organized as follows. Chapter 2 includes the background of main supply chain activities and discusses the resilient supplier selection systems and useful techniques. Chapter 3 introduces the related work and Chapter 4 presents Methodology. Chapter 5 presents the performances and evaluation. Finally, Chapter 6 concludes this work and outlines the potential directions that can be followed to improve it in the future.

CHAPTER TWO

BACKGROUND

2.1 Supply chain system primary activities

We can describe the whole supply chain system into three primary activities: Manufacturing, inbound logistics, and outbound logistics.

2.1.1 Manufacturing

A manufacturer is an individual or a business that creates finished products from raw materials in order to profit[92]. Manufacturing has grown into a more automated, computerized, and intelligent process. Smart manufacturing is a new way of production that integrates today's and tomorrow's manufacturing assets through sensors, computer platforms, communication technologies, control, simulation, data-intensive modeling, and predictive engineering[93]. It makes use of technology system concepts, which are being advanced by the internet of things, cloud computing, service-oriented computing, artificial intelligence, and data science. Once applied, these concepts and technologies will establish smart manufacturing as a defining feature of the next industrial revolution[64]. Six pillars encapsulate the essence of smart manufacturing: manufacturing technology and processes, materials, data, predictive engineering, sustainability, and resource sharing and networking[69]

2.1.2 Inbound logistics and Outbound logistics

Inbound logistics entails the procurement and receipt of products, their processing within the company, and contact between the business and the suppliers. The outbound logistics takes into account both the business-customer relationship and the sales agreements between suppliers and consumers[78, 121].

The planning stage covers all supply chain management, including inbound logistics processes. Inbound processes vary from placing to delivering orders between manufacturers and suppliers [89] and are sub-categorized into three distinct types: strategic, tactical, and operational planning [66]. Strategic inbound logistics is the study of various plants and delivery centers' ability to incorporate emerging goods in the production continuum [66]. Tactical inbound logistics planning emphasizes the coordination of logistics strategies and their assessment [43]. Finally, operational inbound logistics planning occurs when procedures and services are continuously managed prior to the transport [106]. Inbound logistics planners exam and inspect inventories, packaging containers, and in-house transportation to ensure effective inbound logistics processes [66].

The evaluation and choice of concepts mainly focus on transport, storage, inventory costs, service level agreements, and primary performance measures [89]. There is a range of commonly used distribution concepts and frameworks that are employed in inbound logistics. Each of them has demonstrated strengths and weaknesses. A stable and efficient supply is essential to product manufacturers due to the too high uncertainty of markets. External environmental issues can cause unforeseen problems to arise. For example, just-in-time (JIT) and just-in-sequence (JIS) supplies are ubiquitous in the automotive industry [65]. Inventory shall remain at a minimum to decrease storage costs. However, the drawbacks of JIT and JIS systems emerged during the 2016 refugee crisis in Europe. Austria modified its border control protocol, resulting in longer waiting times at the German border. Original Equipment Manufacturers (OEMs) and suppliers considered reorganizing the JIT distribution processes between Eastern European supply plants and OEM plants in Germany based on this external disruption [65].

The other distribution concept is a consolidation hub system where suppliers provide complete full truck load (FTL) or less-than-truckload (LTL) to the consolidation hub and on to the factory. A hub system may be a multi-to-many distribution concept that consolidates products and transfers them to consumers. Hubs require logistic commitment and process handling [30]. An excellent example of many-to-many delivery is the cross-docking method in which several supplier serve multiple plants by pre-packaged goods at a cross-docking point where products are shipped to multiple destinations [30]. This idea of distribution eliminates LTL shipments and they call it a Milk Run transports, which mixed cargoes from multiple sources to one client. Instead of each supplier sending a truck every week to meet a customer's demands, one truck visits the suppliers to pick up loads. The name comes from the dairy business, where one tanker would gather milk from multiple farms and bring it to a processing plant [89]. The final concept is a hybrid system of direct and consolidated shipments—goods sourced directly from suppliers or from consolidation hubs to plants.

Planning and decision-making support for strategic, tactical, and operational issues in inbound logistics processes include a network design[89]. There is no distinct line between certain stages of inbound logistics planning in literature. All stages are in an assembly line manner of planning and production. This will result on the production process and buying sourcing decisions [110]. Especially at the strategic and tactical level, it is important to have knowledge of the system. The statistics of goods and associated materials are complex and subject to adjustment[108] The uncertain environment contributes to the constant need to incorporate content interventions, reports, and performance assessments. Considering the consequences, assessing risks and reviewing strategies and procedures is necessary to reform inbound logistics processes. Increased computational capabilities and the integration of data provide an opportunity for future optimization methods such as device malfunction prediction by machine learning as well as support for extended decision making.

2.2 Resilient Supplier Selection System

The aim of most literature was to achieve efficiency and resiliency in the design and operation of whole logistics system, but at the same time, they want to allow adaptability for changes [66]. A supplier's role in a business is to procure high-quality products from a manufacturer at a reasonable price for resale by a distributor or retailer. The terms 'resilience' and 'robustness' are used interchangeably. In practice, the two phrases are interchangeable, but they might have very distinct connotations in the context of supply chains. The following dictionary-derived definitions have been adopted to enhance clarity in our thinking. 'Robust' has been defined as 'strong or sturdy in physique or build.' Physical strength is the focus here. The ability of a computer system to cope with faults during execution is referred to as 'robustness' in IT[28]. A robust process is desirable, but it does not imply a supply chain is necessarily resilient. In the context of supply chains, we use the term "resilience" as networks. Thus, for resilience we present a dictionary-based meaning anchored on ecosystem science: "The ability of a system to recover to its original condition or move to a new, more desired one after being disrupted." The concept of flexibility is implicit in this description, and given that the desired state may differ from the original, "adaptability" deserves consideration as well. In this section, we provide a concrete base upon which to build knowledge of supplier selection, resilient supplier selection, and its systematic parallel with the related processes of ally-, near-, and multi-shoring.

2.2.1 Supplier Selection:

Supplier selection is the process by which organizations identify, analyze, and negotiate with suppliers. Supplier selection consumes a sizable percentage of a business's financial resources and is important to the organization's success[25]. The main objective of a firm's supplier selection department is to reduce purchasing risk, maximize total value for the purchaser, and create close, long-term relationships between buyers and suppliers. Supplier selection may have wider implications such as increased complexity and diversity, which can result in unsustainable production on the supplier side of the supply chain [4]. Sustainable sourcing strategies recommend that you exclusively purchase from and outsource to efficient and sustainable suppliers[39]. The most sustainable suppliers, on the other hand, may not always be the most efficient suppliers. Other considerations, such as supplier risk, should also be taken into account[9]. It is impossible to accomplish supplier sustainability without the use of a systematic supplier risk assessment approach, which may have negative consequences for the company's reputation if not used properly[40].

SSustainability challenges present themselves as risks in the supply chain, which are ignored by existing risk management systems [55].More importantly, the research on sustainable supplier selection does not adequately take into account supplier risks in real-world applications [126].Risk factors, in our opinion, are the result of supplier selection decisions; thus, it is unreasonable to handle sustainability requirements and risk factors in the same manner. Furthermore, because of the variability of the operational environment, it is unrealistic to assume that all sustainability requirements and risk variables are independent of one another. As a result, the situation becomes very intricate and interconnected [4]. The proposed resilient supplier selection system (RSSS) was built with risk profiles and frequently assesses all suppliers for the continuous improvement of the supply chain.

2.2.2 Resilient Supplier Selection:

Resilient Supplier Selection can be described as the process and outcome of selecting a potential or current supplier that is capable of providing the best support in the face of disruptive circumstances thereby significantly reducing the overall risk of supply chain disruption [3]. To have a resilient supplier we must have proactive strategies, as shown in Figure 2.1 [21]. Firms rely on their ability to accurately predict the likelihood of occurrence and the potential impact of risks or disruptive events. Most supplier selection systems are done manually. In order to systematize the work, organizations usually ask open questions like those found in the Supply Chain Resiliency Assessment Management, or SCRAM, which asks:

- Does the firm have sufficient production capacity to sustain efficient operations in the event of a disruption?
- Does the firm have sufficient financial liquidity to sustain operations in the event of a disruption (e.g., financial reserves)?
- Does the firm have the flexibility to shift rapidly to alternate sources of purchasing, production, and distribution?
- Is the firm's market position in terms of brand equity, and is customer loyalty strong?
- Is the firm significantly invested in innovation and new product development?
- Does the firm have clear visibility into the current status of the business environment?
- Are different functions within the firm effective at collaborating with each other for the firm's benefit?
- Is the firm effective at collaborating with other supply chain participants for mutual benefit?

2.2.3 <u>Ally-Shoring, near-shoring, and multi-shoring:</u>

Ally-Shoring is defined as "the process by which countries rework critical supply chains and source essential materials, goods, and services among and between trusted

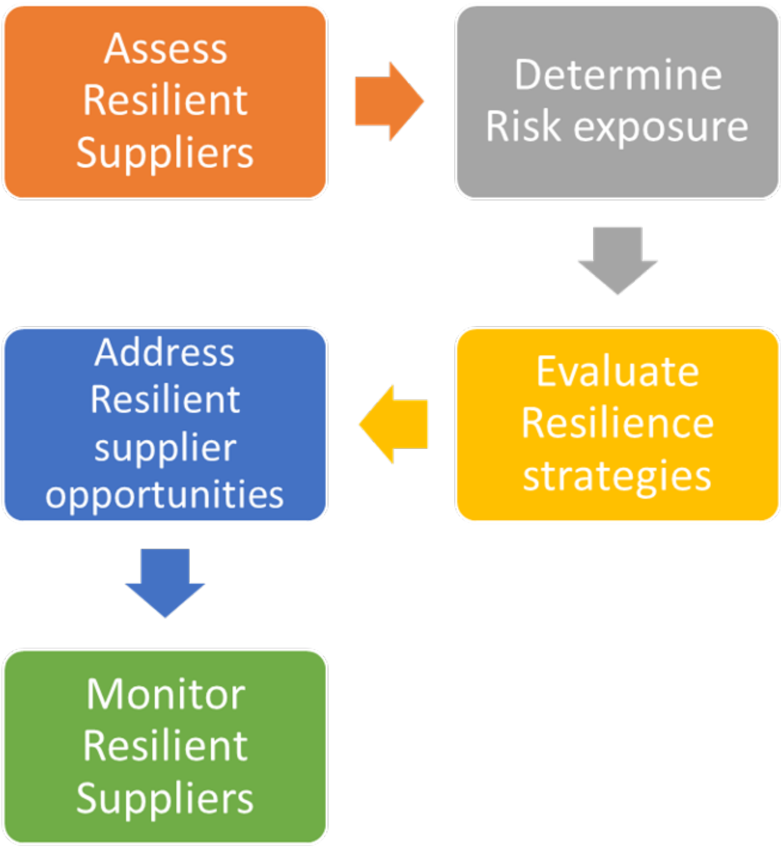

Figure 2.1: Proactive Strategy for Resilient Supplier

democratic partners and allies, with a focus on investing in the short and long-term relationships that protect and enhance joint economic and national security"[27]. Near-shoring is the process of moving a company's operations to a neighboring nation, particularly in preference to a more distant one[47].Near-shoring has many advantages, including cultural similarity, physical closeness, and a more convenient time zone. When it comes to multi-shoring, as the name indicates, it not only offers a risk mitigation strategy, but it also gives a chance to speed up the creation of new processes and products by splitting work across many sites, which is considered resiliency [61]. In the event of multi-shoring, we recommend that companies conduct a thorough review of the following aspects before deciding on a country or a number of countries: (1) The political system; (2) the information and communications technology infrastructure; (3) the regulatory regime; (4) the quality and quantity of the workforce; (5) the judicial and legal system; (6) and the language/culture of the people who live in the country. The following step should be conducted to narrow the scope of the investigation to a specific corporation inside a nation. Elements such as: (1) the match between client requirements and probable vendor capabilities, (2) financial and cost concerns, (3), the supplier's speed and agility, and (4), quality considerations must all be taken into account [61].

To describe and draw an image for the geographical location suppliers and manufacturers opportunity spectrum we recommend reading through table 2.1 which demonstrates suppliers from overseas and focal firms that build everything in house, which is rare and not recommended since they miss the advantage of diversification.

2.3 Supply Chain Risks

Supply chain risks can be classified in a variety of ways and from a variety of angles, such as from the perspective of corporate governance or financial risk agendas, or even from the perspective of a multi-level complex system [96]. Mason-Jones and Towill

Table 2.1 Suppliers and Manufacturers Opportunity Spectrum

Geographical location	Definition
Overseas Suppliers	Supplier in a country out of manufacturer Continent like China for US manufacturers
Near-shoring Suppliers	Suppliers in a country that neighbor to the manufacturers country like Mexico to US
Ally-shoring Suppliers	Suppliers in a country that alliance to the manufacturer’s country like Canada, Panama, Mexico to US
National Suppliers	Suppliers that inside the manufacturers country like supplier in Arizona for manufacturer in Ohio
Regional Suppliers	Supplier that located in the manufacturer region for example supplier and manufacturer in the Mid-west
Local Suppliers	Supplier exist in the town or the state of manufacturer
Focal Firm	Supplier and Manufacturers are on entity and it is rare

offered a starting point for categorizing risks[79]. There are three categories of risk that can be further subdivided to give a total of five categories:

- Internal to the company-Process
- Internal to the company-Control
- External to the firm but internal to the supply chain network-Demand
- External to the firm but internal to the supply chain network-Supply
- External to the network-Environmental

2.3.1 Categorized Risks

Each of these five categories is briefly detailed in the sections that follow:

- Processes:

  Are the sequences of value-adding and managerial actions carried out by the organization[114]. The execution of these activities is likely to be dependent on assets that are owned or controlled by the company, as well as on a functional infrastructure. It is important to carefully assess the assets that are owned or managed internally, as well as the dependability of supporting transportation, communication, and infrastructure. Process risk is concerned with the possibility of interruptions to certain processes [91].

- Controls:

  Are the underlying assumptions, rules, systems, and procedures that regulate the manner in which an organization exercises control over the processes[130]. Order quantities, batch sizes, safety stock policies, and other supply chain parameters, as well as the policies and procedures that govern asset and transportation management, are examples of what is meant by supply chain parameters. The risks associated with the application or misapplication of these regulations are therefore referred to as control risks [114].

  The next two categories are external to the focus firm, but they remain internal to the inter-organizational networks through which materials, goods, and information are transferred from one organization to another [79]. As a best-case scenario, the focal firm should be aware of any prospective or actual disruptions to the planned flow of goods and information from within and between each node or link in the supply chain networks through which its own value-streams pass [16]. Although this may not be achievable in practice, the focal firm should at the very least make an effort to get aware of the risks that are known to or are expected to harm neighboring organizations [68]. Although it is doubtful that the focus firm would ever have comprehensive knowledge of all potential risks, good monitoring should improve the possibility of such events occurring and provide early warning when they do [68].

- Demand:

  Risk refers to the possibility or occurrence of disruptions in the flow of goods, information, and in this case cash, that originate within the network and travel between the focal firm and the market [118]. In particular, it is concerned with the procedures, controls, asset and infrastructure dependencies of the organizations that are downstream and adjacent to the focus firm and its assets [14].

- Supply:

  Risk is the upstream equivalent of the risk described above; it is concerned with prospective or actual disruptions in the flow of goods or information emerging from inside the network, upstream of the focus business, and it is associated with the supply chain [97].

  The fifth and final type of disruptions is comprised of events that occur outside of the network of organizations through which the value-streams/product supply chains are channelized.

- Environment:

  This occurrences may have a direct effect on the focal firm, on those upstream or downstream, or even on the marketplace as a [90]. They may have an effect on a specific value stream (e.g., product contamination) or on any node or link in the supply chain (e.g., as a result of an accident, direct action, harsh weather, or natural catastrophe). They may be the result of geopolitical, economic, or technological developments occurring thousands of miles or across several organizations from the focus firm's supply chains, but may have spillover impacts via linkages to other industry networks [51]. While some of these events may be predicted in terms of their kind or timing (e.g., those resulting from regulatory changes), many may not, even though their influence may still be estimated.

Another factor that contributes to supply chain risk is that upstream and downstream 'visibility' is sometimes quite limited. In other words, information is routinely exchanged in a limited fashion between adjacent units in a network [125]. For example, a supplier to an original equipment manufacturer (OEM) may be unaware of the company's sales volume, receiving only infrequent orders with the expectation of fulfillment within an ever-shorter time frame. The reality is that the majority of organizations are "forecast-driven" rather than "demand-driven," forcing them to make decisions in isolation[85]. While this absence of shared knowledge adds tremendous cost to the supply chain as a whole, it also adds enormous vulnerability.

Frequently, there is a major "gap" between the formulation of corporate strategy and the realization of the impact of such strategies on supply chain vulnerability in organizations [63]. For instance, many businesses have shifted from domestic to global sourcing in search of reduced unit prices. However, that definition of cost is too narrow; it often overlooks the increased risk to the supply chain caused by extended/lead times, reliance on partners who may be sensitive to external events, or the potential loss of control [128].

As a result, many organizations were unable to quickly identify acceptable tools and approaches for managing the plethora of potential dangers. Additionally, while most larger firms have some sort of business continuity planning, business continuity management has been sluggish to incorporate risks arising from the broader supply/demand network [60]. We argue many of the risks to business continuity originate beyond the focus firm, necessitating the need for a much broader perspective when it comes to contingency or continuity planning.

What steps should be performed in light of these findings? Achieving a more resilient supply chain is the way forward. There are a number of distinct concepts that support supply chain resilience that have emerged as a result of our study effort [21]. In fact, most of them reaffirm rather than deviate from commonly established principles of good supply chain management [6]. First and foremost, it appears that resilience should be built into these systems. In other words, there are certain characteristics that, if incorporated into a supply chain, can make it more resilient to disruptions and risks [3]. Second, because supply networks, by design, will typically span multiple corporate entities, a high level of collaboration will be required to effectively identify and manage risks in the supply chain. Third, resilience is a synonym of adaptability; in an uncertain climate, being able to react rapidly to unexpected events is unquestionably a unique advantage [23]. Finally, the development of a risk management culture within the organization will improve, if not entirely enable, the resilience of the supply chain [89]. What needs to be acknowledged and implemented is that the greatest threat to company continuity may very well come from the wider supplier chain rather than from within the business itself.

2.3.2 Collaboration in the Supply Chain

Since supply chain vulnerability is a network-wide concept by definition, risk management must be applied throughout the whole supply chain [50]. Collaboration initiatives across supply chains may make a significant difference in risk reduction efforts. The ultimate objective is to create the circumstances that will allow for collaborative work to take place [5]. Historically, supply chains have been characterized by interactions that are at least arm's length, if not antagonistic, between the different members [54]. Information sharing with suppliers and customers has never been a part of company history. However, there have been encouraging signs lately that a greater willingness to interact is rising in a number of supply chain organizations [131]. Through Collaborative Planning, Forecasting, and Replenishment (CPFR) activities, there is now a significant amount of cooperation between manufacturers and retailers in the fast-moving consumer goods (FMCG) business [80].

The core idea of collaborative supply chain work is that information exchange can help reduce uncertainty [107]. Thus, a critical objective for supply chain risk reduction must be the establishment of a supply chain community that enables the interchange of information among its participants [33]. The objective is to establish a high level of supply chain intelligence, in which upstream and downstream risk profiles are more visible.

Supply chain intelligence is a term we invented to refer to the practice of utilizing knowledge generated and shared by supply chain partners [109]. The type of knowledge that can contribute to the development of supply chain resilience is that which identifies risk and uncertainty sources at each node and link in the supply chain [58]. Additionally, supply chain expertise can be classified as Strategic, Tactical, or Operational[44].

Strategic knowledge is the understanding of emerging trends and difficulties that may have an impact on the continuity of a supply chain in the future[84]. This category of 18 knowledge can be developed through formal "P.E.S.T." (Political, Economic, Social, and Technological) analysis [96]. These assessments are meant to facilitate the formalization of an assessment of the environment in which networks and supply chains operate[74]. At the tactical level, the required expertise is focused on risk assessment for present operations; specifically, demand, supply, process, and control risk[66]. The third degree of expertise is operational and is concerned with the management of the business on a day-to-day basis. Supply Chain Event Management (SCEM), a newly emerging topic, has the potential to be extremely beneficial in this aspect[96].

2.3.3 Agility

Agility in the supply chain can be described as the capacity to react fast to unforeseeable changes in demand or supply[2]. Numerous organizations are at risk due to their inability to respond quickly enough to changes in demand or supply disruptions. Enterprises as well as networks may benefit from agility, which has many different characteristics. Having agile partners both upstream and downstream of the focus company is crucial to the responsiveness of the focus firm in an agile environment[119]. 'Visibility' and 'Velocity' are two critical components of agility.

Visibility of the Supply Chain: Visibility in the supply chain is the ability to see from one end of the pipeline to the other[60]. Visibility, for example, entails having a clear picture of upstream and downstream inventories, demand and supply conditions, as well as production and purchasing schedules. Additionally, it implies internal transparency through open lines of communication and agreement on a "single set of numbers" [86]. The presence of intervening inventories upstream and downstream of the focal firm can obscure visibility in a supply chain [87]. These intervening inventories are typically established independently of one another as a result of obscure decision criteria. Visibility will be further distorted by the bullwhip effect, which magnifies tiny changes in market demand as it goes up the supply chain [124].

Supply chain visibility can only be achieved through tight engagement with customers and suppliers, as well as through internal integration within the organization [91]. Collaborative planning with consumers is critical not only for gaining visibility of demand, but also for sharing knowledge about market trends and risk perceptions [83]. Similarly, upstream visibility involves extensive collaboration with suppliers and the use of “event management” logic to enable the signaling of potential supply disruptions. A substantial impediment to supply chain visibility frequently arises from the target firm’s internal organizational structure [75]. The existence of “functional silos” obstructs the free flow of information, resulting in “second guessing” and an overall lack of communication [19]. This problem is frequently worsened when a business has internal suppliers or customers with insufficient integration. The main purpose of increasing supply chain visibility is to dismantle these silos and establish cross-functional, multidisciplinary process teams.

Supply chain velocity is the second component of supply chain agility. Velocity is defined as the ratio of distance to time [1]. As a result, time must be shortened to enhance velocity. The term “end-to-end” pipeline time refers to the overall amount of time required to move product and materials from one end of the supply chain to the other. End-to-end pipeline time can be defined in terms of agility as the time period from when the focal firm places orders with its first tier suppliers to when it delivers the final product to its customers [116]. Acceleration is critical to the development of agile supply chains [113]. In other words, how quickly can the supply chain respond to changes in demand, whether positive or negative?

Effective supply chain velocity and acceleration are built on three key foundations: streamlined procedures, reduced inbound lead times, and the elimination of non-value added time.

- Streamline processes are those that have been created to minimize the number of stages or activities required to perform operations in parallel rather than serially, and to be electronic rather than paper-based. These streamlined processes are simultaneously optimized for small batch sizes, whether they are order amounts, production batch sizes, or shipping batch sizes. The emphasis is on adaptability rather than scale economies [56].

- Reduction in inbound lead times is the second critical component of increased supply chain velocity. One of the selection factors for suppliers and sources of supply should be their capacity to respond quickly to delivery requests and to accommodate short-term changes in volume and mix requirements [3].

  Schedule synchronization based on shared information helps suppliers to become more nimble without relying on inventory as a buffer, with all of its associated issues.

- Non-value-added time refers to the majority of time spent in the supply chain that does not bring value to the client. Typically, idle time, (i.e. inventory), is the culprit. That inventory is generated as a result of inefficient procedures — each day of process time necessitates at least one day of inventory to cover the lead time [117].

2.3.4 Building a Culture of Supply Chain Risk Management

Similar to how many businesses recognized that the only way to make Total Quality Management (TQM) a reality was to cultivate a culture that prioritized quality, there is a demand today to cultivate a risk management culture within business [96]. We would suggest that this risk management culture should be expanded beyond corporate risk and business continuity management to include "supply chain continuity management" [111].

As with every situation of corporate culture change, nothing is achievable without sound leadership from management. One of our study's primary results is that supply chain risks pose the greatest danger to business continuity, yet, ironically, not every organization has supply chain management represented in its own right in the boardroom. If the supply chain has a voice at that level, it is frequently represented by information systems/information technology directors or vice presidents [104]. While this approach is sometimes effective, it frequently results in a restricted knowledge of what defines supply chain risk from an information systems perspective [96].

Additionally, one may argue that supply chain risk assessment should be a formal component of all decision-making processes [11]. Thus, when developing new goods, supply chain vulnerabilities, such as component availability and lead times, should be considered. Similarly, when there is a change in business strategy, such as a shift from domestic to offshore sourcing, the ensuing supply chain risk profile should be reviewed [96].

A supply chain risk management team should be established within the firm with the responsibility of updating the supply chain risk register on a regular basis and reporting to the main board via the supply chain director [96]. At a minimum, we suggest this occurs on a quarterly basis.

CHAPTER THREE

SUPPLIER SELECTION CHALLENGES AND RELATED WORK

3.1 Supplier Selection issues

In this section, we will go over the common challenges for supplier selection in general and its consequences in the related entities. Strikes, civil unrest, natural disasters, sanctions, trade war, and pandemics are the challenges supply chain systems face today. When such crises occur, supply chains—particularly those which depend on international trade—are the most severely affected. Systemic supply chain flaws have recently been exposed, and although all firms suffered, those that had not kept up with essential supply chain developments were the most severely harmed [115]. Looking forward, as businesses struggle to re-establish supply lines and begin operations, they must consider the critical supply chain issues that they will face regularly.

3.1.1 Data with Insufficient Depth

When China closed its borders during the onset of the COVID-19 pandemic, many companies who believed they were familiar with their supply chains learned that knowing merely Tier 1 suppliers was not enough to remain competitive [46]. Few realized the degree to which the closure of Tier 2 and Tier 3 suppliers in the Wuhan area, and subsequently elsewhere as the virus spread to other parts of the globe, would have an impact on the availability of goods on the market [31]. Much of this was caused by erroneous assumptions about Tier 1 suppliers, perhaps as well as wishful thinking on the part of the company. In order to discover risks and weaknesses in supply chains, it is critical that enterprises map out their supply chains in great detail. When lower-level supplies are jeopardized, this knowledge will enable swift and decisive action.

3.1.2 Supply Chain Risk Rises of Single-Source Sourcing

There are a variety of reasons why many businesses have chosen single-sourcing strategies. One of the most common reasons is that it is regarded to be the most cost-effective option [20]. However, unfortunately companies are exposed if suppliers experience shortages or manufacturing disruptions, as is the case in the current global economic situation [132]. A single source of supply in a complex environment, where supply chain issues such as those described above are common, is a hazardous strategy that almost always results in sales losses when there is an interruption. Instead, businesses should concentrate on risk mitigation solutions that allow them to predict and diminish supply chain difficulties and dangers before they occur [11].

3.1.3 Slow Digital Transformation

It is critical to have access to data in order to make successful decisions [112]. Unfortunately, many businesses have a jumbled collection of manual and digital systems that effectively trap information inside functional silos, resulting in decision-making being inhibited by an inadequate view of the situation at hand [82]. n order for businesses to have access to supply chain data, it is critical that technologies that enable data to move freely across the system be developed and implemented. Additionally, enterprises need technology such as a supply chain digital twin, which enables them to monitor, control, and observe the consequences of their actions and the decisions of others [18].

3.1.4 Continuing with Traditional Inventory Management Strategies

Traditional inventory control systems base current inventory tactics on historical success to maximize profits [70]. To identify specific needs, precise methods are utilized. There is a problem with this method in that it does not take into account unforeseen developments, nor does it allow for flexibility, and it is frequently out of touch with current circumstances [7]. An outside-in approach to supply chain concerns that examines the use of streaming data to develop insights, detect market fluctuations, and define demand is being explored [34]. This, in conjunction with the next generation of sophisticated inventory optimization approaches, may be able to assist businesses in coping with uncertainty more effectively than typical inventory optimization systems do currently.

3.2 Supplier Selection Strategies in SME Supply Chain

Small and medium-sized enterprises (SMEs) are a vital and critical component of any supply chain, both in terms of their numerical functionality and the large array of products that they offer[10]. The fact that large corporations are unable to manufacture each component in-house means that they frequently outsource sub-assembly parts to small and medium-sized businesses. SMEs are frequently found to exploit new goods and swiftly disperse new technology in the market, and to do so at competitive costs [42]. However, these tiny businesses are hampered by a lack of resources and financial restraints.

Selecting the most appropriate supplier entails much more than simply comparing a variety of price lists. The decision will be influenced by numerous aspects, including price, quality, dependability, and service [102]. The relevance of each of these variables will be determined by the priorities and strategies of the organization [10]. Strategic supplier selection may also assist in better understanding how the potential clients consider the pros and cons of different options when making purchases [21].

1. When picking suppliers, it is important to think strategically:

   Suppliers that provide products or services that meet the demands of a company are considered to be the most effective [49]. As a result, while searching for suppliers, it is preferable to be certain of the business requirements and the goals we want to achieve through purchasing rather than just paying for what suppliers want to sell [122]. However, it is also critical to have a variety of sources to choose from; buying from a single provider might be risky since we don't know where to turn if they disappoint or even go out of business. Likewise, although exclusivity may encourage certain suppliers to provide companies with a better service, others may become arrogant and lower their standards as a result of the exclusivity [59].

2. What characteristics to look for in a supplier?

   Reliability: Keep in mind that if they fail, the firm will fail, leading the customer of the firm will fail as well. Quality: The consistency of the quality of the supply is critical since the customer will link bad quality with the firm rather than with its suppliers [12]. Excellent value for money: The cheapest price is not necessarily the greatest deal in terms of overall value for money. For the firm suppliers to be dependable and high-quality, firms must decide how much they are ready to pay for their products and what kind of balance they want to strike between cost, dependability, high-quality products, and customer service [101]. Excellent customer service and clear communication: The firm relies on its suppliers to deliver on time, or at the very least to be honest and provide ample notice if they are unable to do so. The top suppliers will want to speak with the firm on a frequent basis to learn about their requirements and how they can better assist. Having financial security is important: It is usually a good idea to double-check that the supplier has a sufficient amount of cash on hand to supply what the firm needs when it needs it. A credit check will assist the firm in ensuring that they will not go out of business when their services are needed the most [35]. A method based on collaboration: Both parties will profit from a solid working relationship. The firm wants its suppliers to recognize how important the firm is to them, so they will go to great lengths to provide the greatest service possible. Showing suppliers how essential they are to the firm can increase the likelihood of receiving a positive reaction from them [32].

3. Identifying potential suppliers is essential:

   Suppliers can be found through a variety of channels, including recommendations, directories, trade associations, business advisers, exhibitions, and trade press.

4. Creating a shortlist of potential supplier:

   An open question can help to narrow down the shortlist of possible suppliers for the company [48], such as: Are these suppliers capable of delivering what the firm wants when it is required? Are they in a stable financial position? How long has the company been in operation? Do we know any other companies who have used them and would be willing to recommend them? Is it possible that they are on any approved supplier lists maintained by trade associations or the government?

5. A supplier should be selected:

   The following stages are involved in selecting a supplier: obtaining a quotation, comparing possible suppliers, and finally negotiating pricing, terms, and conditions [3].

6. Choosing the most appropriate supplier for the firm:

   Identify what the firm needs from a supplier and distinguish between strategic and high-value raw material suppliers and non-strategic suppliers who deliver low-value supplies. Qualities also including dependability, service, agility, and pricing are often vital for most businesses when selecting a supplier [21].

Buying from too many suppliers is hard to manage and less cost-efficient as most manufacturers and businesses practice. This is especially true for suppliers that provide minimal value-added services. On the other hand, having one supplier is also dangerous [127]. The value of having an alternate supply source available to assist in hard times cannot be overstated. This is truly essential when dealing with suppliers that are critical to the success of a company [15]. This was the logical structure and traditional way companies selected suppliers. Nowadays, there are dynamic solutions that save firms' time and employees from engaging in such long processes. In addition, the agile and dynamic system of selecting a supplier can focus on examining the supplier's ability to adapt to interruptions and market challenges [2].

3.3 Related Work

This section briefly reviews the recent studies on addressing the supplier selection systems and their risks. Previous work relating to our approach is discussed in this section. In the supplier selection, the majority of studies investigate diverse applications of decision-making approaches through three perspectives: multi-criteria decision-making, mathematical programming, and artificial intelligence [22].

Guo et al.[45]introduced a strategy based on the performance support vector machine (P-SVM) combined with the decision tree (DT), which is implemented by changing the supplier selection issue into a multi-class classification problem. The results obtained as a consequence of using it not only provide a classification function, but also a list of the most "informative" criteria, which are represented by features picked from the original criteria. As a result, the suggested strategy enhances performance in the following two ways: first, it reduces the number of errors. The introduction of hierarchical structure significantly reduces the number of binary classifiers. The hierarchical structure is built using an updated Kruskal method to increase classification accuracy while simultaneously reducing compute consumption. Second, the most "informative" features are picked by P-SVM for inclusion in classifiers, resulting in a significant improvement in generalization performance. Furthermore, the computing consumption is decreased even further as a result of the reduction in the number of characteristics that are used to the actual categorization. Experiments conducted on data from China demonstrated both the methods of the suggested technique and its benefits over regular SVM in terms of performance.

Nourbakhsh, Ahmadi, and Mahootchi[95].developed a system for taking supply risks into account when selecting suppliers. Based on their system, the expert assesses the reliability of each procurement element in light of some risk considerations that have been offered. After that, the Multi-Layer Perception (MLP), a proper nonlinear function approximation methodology, is trained on the network to take on the function of an expert opinion when calculating the reliability of the estimates. Additionally, the data envelopment analysis (DEA) is defined as the weighted sum of outputs to the weighted sum of inputs for a specific Decision Making Unit (DMU), which takes into consideration the standard selection criteria, including the price, delivery time-frame, quality, and production capacity. The efficiencies are then paired with the reliability scores to identify providers who are not dominated by one supplier.

A.Chen et al.[23] discovered and gained useful insights that are applicable to the automotive industry through the use of weighted goal programming (WGP) and preemptive goal programming (PGP) techniques. The results of the study included: (1) When enhancing performance business strategies, senior management teams should consider global supplier selection; (2) One market in the Asian region was identified as a potential additional supplier; (3) Senior management teams should consider global supplier selection when developing long-term business strategies. The World Resources Institute (WRI) is a top focus. Furthermore, this research demonstrated that supplier selection and crisis risk assessment are critical components of any long-term business strategy.

A study of grey relational analysis approach was conducted by Rajesh and Ravi[100]. When a supplier is chosen in the context of a resilient supply chain, the supplier is referred to as a resilient supplier. As an example, consider an electronic supply chain with six different suppliers. In this study, grey possibility values for supplier selection were determined and the providers were then prioritized based on their importance. Additionally, a sensitivity analysis was carried out to determine how much the selection priorities of suppliers change when the weightings assigned to each of the resilience traits are varied.

R R. Levary[72] evaluated and ranked potential suppliers, and his process point incorporated both tangible and intangible factors that must be used. Furthermore, because multiple manufacturer's executives may wish to be involved in the decision-making process, and because each may have a different judgment regarding the subjective criteria, a methodology for evaluating and ranking potential suppliers that incorporated the input of multiple decision makers was required to make informed decisions. These expectations were met by employing the Analytical Hierarchy Process (AHP) technique in both cases.

Alikhani et al.[4] examine a supplier selection issue in which the criteria for selection include the triple bottom line (the economic, social, and environmental elements of sustainability), as well as supplier risks. Also the developed a framework that takes into account both a risk-averse approach to the selection problem as well as a risk-neutral approach to it. They first use an extension of a group Multiple criteria decision tool (i.e. Tra-IT2F VIKOR) to quantify decision-maker inputs and outputs, then use a form of super-efficiency DEA (Data envelopment analysis) , which is non-parametric mathematical programming technique, to choose the best supplier from among a pool of candidates. The application was on the basis of a real-world grocery chain in Iran, they demonstrated a multi-method approach. Demonstrating that subjectivity is inherent in the majority of real-world issues, but that decision makers may still make rational and objective choices by using their quantification technique and the DEA model. According to their findings and sensitivity analysis, addressing sustainability criteria and risk variables separately vs concurrently has a significant impact on the selection process in a positive way. Risk variables that have been assessed based on qualitative information (i.e. the intuitive judgment of DMs). However, if risk measurements are based on objective historical data when such data is available, the dependability of the results will undoubtedly increase.

Ravindran et al.[103] Essentially, they describe the risk-adjusted supplier selection problem as a multi-criteria optimization problem, which they then solve in two phases. In Phase 1, which is also known as pre-qualification, a large number of initial supplier are reduced to a smaller number of controllable vendorsor supplier through the use of various multi-objective ranking systems. Order quantities are distributed among the suppliers that have been short-listed in Phase 2 through the use of a multi-objective optimization model. In the multi-objective formulation, price, lead-time, VaR-variance-covariance type risk of disruption due to a natural disaster, and MtT type risk of quality are explicitly regarded as four competing objectives that must be minimized simultaneously in order to get the best overall result. Aside from that, they tackle the multi-objective optimization problem by employing four different forms of the goal programming technique. The models are demonstrated through the use of a real-world application for a worldwide information technology corporation.

A decisions model for supplier selection has been presented by Amin et al.[6], which is divided into two phases. Suppliers are evaluated in the first phase using a quantitative SWOT analysis (Strengths, Weaknesses, Opportunities, and Threats) to determine their suitability. A combination of linguistic variables and triangular fuzzy numbers is utilized to quantitate variables. A fuzzy linear programming model is used to determine the order quantity in the second phase of the process. In five fold , the model studies the supplier selection problem from a strategic perspective, which is one of its most significant innovative aspects and merits: first, the model investigates the supplier selection problem from a strategic perspective. Second, fuzzy logic has been used because it is capable of accounting for uncertainty in human beliefs. Furthermore, it is thought that demand is a nebulous quantity. Third, for the first time, fuzzy logic and quantitative

SWOT analysis have been integrated. Fourth, both quantitative and qualitative elements have been addressed in this study, as well as other considerations. Fifth, as restrictions in the mathematical model, the capacity of the warehouse and the minimum order quantity are taken into consideration as well. This algorithm is simple to build using a spreadsheet tool, and its computation is rather quick as well.

Cavalcantea, Frazzonb, Forcellinia, and Dmitry[21] presented hybrid technique to build combines simulation with machine learning and to investigate its potential applications in data-driven decision-making support for resilient supplier selection. additionally consider on-time delivery as a sign of supplier reliability, and investigate the circumstances influencing the establishment of resilient supply performance performance profiles. The theories of risk profile of supplier performance and resilient supply chain performance are then theorized by the researchers. They have demonstrated that their technique is effective in understanding the relationships between deviations from the robust supply chain performance profile and the risk profiles of supplier performance. In conclusion, the findings imply that, when appropriately used, a combination of supervised machine learning and simulation can increase the reliability of delivery. It is also useful for examining the supplier base and un-covering the critical suppliers, or combinations of critical suppliers, whose interruption results in detrimental performance declines, as described above. The findings of their work contribute to a better understanding of how and when machine learning and simulation can be coupled to create digital supply chain twins, and how these twins can be used to improve supply chain resilience.

Table 3.1 Related work comparison

Work	Risk Measurement	Approached Method	Size of Supply
Cavalcantea et al. [21]	Data-Driven	Machine Learning	SME
Amin et al. [6]	Not at all	Fuzzy linear programming	SME
Ravindran et al. [103]	Historical Data	MCDM	SME
Alikhani et al. [4]	Historical Data	MCDM and MP	SME
R R. Levary [72]	Historical Data	AHP	SME
Rajesh and Ravi [100]	Historical Data	Gray Relational Analysis	SME
A.Chen et al. [23]	Historical Data	WGP and PGP	SME
Nourbakhsh et al. [95]	Historical Data	MLP and DEA	SME
Guo et al. [45]	Historical Data	Machine Learning P-SVM , DT	SME

There are a variety of methodologies and strategies that fit under the umbrella term of artificial intelligence. In this finding we classified into five major categories, each of which will be discussed further below:

- Strategy that relies on some type of mathematical optimization.
- Network-based techniques, in which issues are represented as a set of alternative states with transitions between them are used.
- Techniques that use agent-based modeling and multi-agent system interaction as part of their design.
- Techniques that employ some type of automated reasoning based on previously acquired information are considered.
- Techniques using machine learning and big data analytic.

Exploiting these techniques can lead to a variety of interesting applications in the field of supply chain risk management, including, but not limited to, risk-aware automated supplier selection, risk propagation modeling in a supply network, identification and prediction of deceptive supply chain practices, data-driven explanation of disaster resilience, and end-to-end decision support to facilitate collaborative disruption management, among other things.

CHAPTER FOUR

METHODOLOGY

This chapter described our research methodology techniques, which included creating a resilient supply chain system in general and the main concepts, using Machine Learning Techniques (ML), and describing risk profiles and the evaluation for each supplier. The Dataset that we used is then introduced. Finally, the Implementation section brings this chapter to a close.

4.1 Introduction

Advanced technologies made the supply chain more adaptable for changes. The dynamic systems raised the dependency on the machine and less on the human. Because advantage of the technology revolution, the rate of error have decreased with the time systems and technologies have advanced. Afterword, the new technology, especially artificial intelligence and its application on machine learning help visualize and predict for better dynamic supplier selections systems. Machine learning algorithms have the ability to detect the resiliency level for a supplier. In addition, machine learning algorithms can assess the risk level of a supplier.

Supply risk is an umbrella word that refers to a variety of factors that impact the incoming flow of products or services, such as supplier failures, late deliveries, quality issues, financial instability of suppliers, and ineffective supplier relationship management techniques[38].Disruptions in production, customer discontent, financial losses, sales loss, harm to a business brand, and bankruptcy are all hazards associated with suppliers that may have major effects for manufacturers and their whole Supply Chain networks[77].

The challenge of selecting and assessing suppliers is a multi-criteria problem that is expanding in scope and significance. With the availability of cutting-edge technology for monitoring, measuring, and comparing multiple characteristics of a supplier, companies may profit from a simple and effective framework for selecting suppliers using multi-criteria decision-making procedures. Emphasizing the firm's aims and business requirements when selecting a supplier will be crucial to the success of any organization. As a result of business efforts such as outsourcing, globalization, and lean manufacturing, there is an increased reliance on suppliers. While this emphasis on the firm's basic principles is critical, a successful methodology for comparing supplier performance must be straightforward and standardized for usage across many sectors. Supplier selection procedures that are integrated and customized are critical since they assist firms in selecting the most suitable and efficient providers. Utilizing supplier selection techniques guarantees that businesses engage with the best suppliers who are capable of meeting their unique requirements. Supplier efficiency is measured not just in terms of cost and the capacity to provide high-quality items on time, but also in terms of other critical criteria such as trust, financial competence, and the supplier's historical reputation. However, there is a lack of congruence between supplier selection and supply chain strategic decision making in the current literature, as academics have placed an excessive emphasis on the use of quantitative optimization models in supplier selection. As a result, there is an urgent need for researchers to close this gap. Before picking the most suitable supplier, businesses should consider their desired level of performance.

Finally, more models utilizing value-based multi-criteria decision-making strategies are needed to solve the challenge of supplier selection. This is because the approach enables the supplier's structure and capabilities to be integrated with the firm's requirements. In the current research on supplier selection, methodologies such as DEA are preferred over value-based procedures due to the decision maker's increased engagement. However, from a practical standpoint, defining the appropriate objectives and key performance indicators with the cooperation of decision makers is more critical to a corporation than using computationally sophisticated approaches to improve supplier selection. The purpose of this chapter is to improve the quality of the supplier selection process in the industry by presenting a framework based on existing multi-criteria decision-making techniques that provides insight into trade-offs, increases confidence (or emphasizes risk) in the decision, and documents the process. The offered framework may be utilized by businesses to evaluate new suppliers throughout their supplier selection phase, as the Excel application is simple to use.

4.2 Methodology

The main goal of this research was to minimize the gap in two identified problems in supplier selection. First, the resilience of suppliers was overlooked. Second, SME manufacturers disregarded the risk level of suppliers. Therefore, the proposed resilient supplier selection system (RSSS) framework utilized six-steps works in parallel statically and dynamically detected problematic suppliers. The objective was to predict the level of resiliency of any supplier entering the system and determine the risk level of all suppliers. In addition, the system provided a better visibility for decision maker of weakness and strength of every supplier. The supplier data checked once entered the system if analyzed or not. Then, if not analyzed static analysis techniques were applied to extract information related to supplier based on its historical data. Generation of resiliency level based on fulfillment rate was applied to the supplier. Then, the risk level was generated using managerial and quantitative methods such as Supply chain operation reference (SCOR), Key performance indicators (KPI), Swing weighting, and probabilistic risk assessment. Then, dynamic steps utilized different supervised machine learning techniques applied on the data that integrated for resiliency and risk levels of suppliers to obtain supplier resiliency level of every supplier. Validating the results the most important step in the system. Afterword, the manufacturer reported and restored the results in the database. The design of (RSSS) system model and the implementation were elaborated as follow:

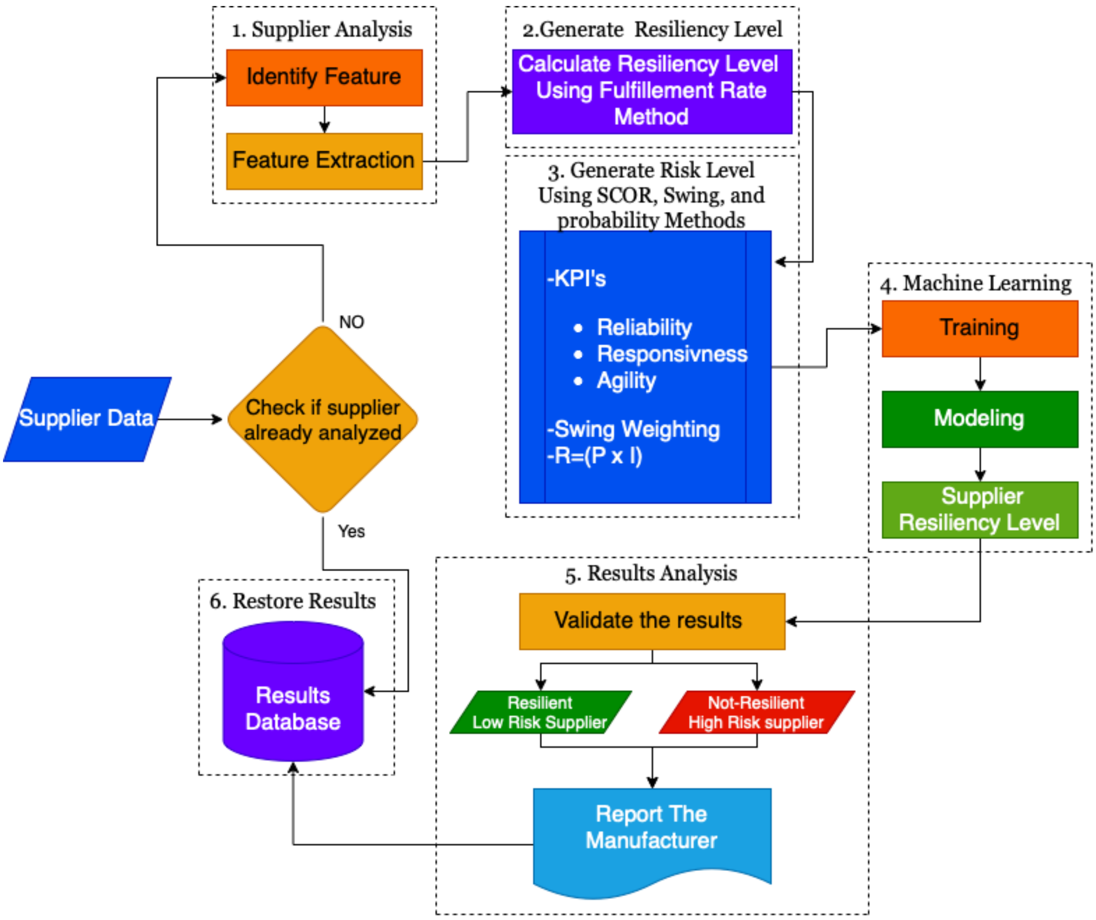

Figure 4.1: System Model

4.2.1 System Model

Resilient supplier selection system (RSSS) was developed with aim to mitigate the risk of suppliers and determine the resiliency level of a supplier for SME manufacturers. Therefore, RSSS consist of two main processes: static and dynamic, as seen in Figure4.1. First, static processes are lightweight conditions running on every supplier data to analyze the supplier and generate resiliency level based on the available feature and fulfillment rate. Then, static process RSSS generates risk level using SCOR method and its KPI's , swing weighting, and probabilistic risk assessment. Second, dynamic process start with supervised machine learning algorithms integrating the risk level of a supplier to result with supplier resiliency level then validating the results, report the manufacturer, and restore the results into the database. The whole process of this system consist of six main stages as follows:

1. Supplier Analysis Stage: examining and analyzing supplier data from its previous data using the static analysis technique to identify available features. Then extracting the usable features of suppliers such as delivery lead-time, capability, distance or location, delivery method, incoming quantity, PO quantity, and agility. This stage could be called the pre-processing stage. This stage aids in identifying the features that can have an effect on the results.

2. Generate Resiliency Level Stage: static process of the analyzed supplier system can generate resiliency level of supplier based on fulfillment rate, Equation 4.1 shows how to calculate it.

$$ResiliencyLevel = \frac{IncomingQty}{POQty} * 100 \tag{4.1}$$

3. Generate Risk Level Stage: is static and dynamic stage we apply Supply chain operation reference (SCOR) as managerial methods conclude on using Key performance Indicators such as reliability, responsiveness; and agility on the supplier features data. Then swing weighting methods were determined based on delivery lead time, capability, and agility of suppliers. Then both methods were integrated to produce the probability of disruption occurrence of supplier which obtained dynamically with the supervised machine learning algorithms multiply by the impact which was in our case the resiliency level as the Equation 4.2 of probabilistic risk assessment compute.

$$(R) = (P)X(I) \tag{4.2}$$

4. Machine Learning Stage: Supplier static data is training the machine learning, then modeling in suitable regression algorithms. Then, the system will determine the best function based on the testing step and generate the resiliency level of each supplier.

5. Results Analysis Stage: Here we validate our results whether the supplier is resilient by indicating low risk on its process of supplying, or not resilient as obviously indication of high risk on its processes of supplying the manufacturer. Validation is done using median square error, root mean square error, and R2 score metrics. As the last phase in this stage, the system report the manufacturer of the supplier resiliency level and detailed explanation of a supplier weakness.

6. Restore Results Stage: all analyzed suppliers' report will be stored in the results database. Therefore, for any new supplier, RSSS will first check the existence of the supplier analysis in this database.

4.2.2 Implementation

In this section, the design and implementation of RSSS are discussed in more detail by elaborating the technical details of each stage. As discussed previously, RSSS stages are statics and dynamics combined. First, second, third, and sixth are static stages while fourth and fifth are dynamic stages:

1. Statics Stages: A detection system, called RSSS, is developed which can apply to any SME supplier. This system allows the manufacturer to submit supplier data to analyze risk and indicate resiliency level. Also, it provides the manufacturer with analysis report about the submitted supplier.

    (a) Suppliers' data enter the system and condition check apply if supplier already analyzed or not, if analyzed already the supplier entry will be restored in the database, if not will move to the supplier analysis stage.

    (b) First, using the static analysis technique, examine and analyze supplier data from previous data to identify available features. Then, using the functional features of suppliers such as delivery lead-time (including incoming quantity and PO quantity), capability, distance or location, delivery method , and agility are extracted from the data. This stage might be referred to as the pre-processing stage. This step assists in the identification of characteristics that may have an impact on the findings.

    (c) Second, given that the static process of the examined supplier system is capable of producing a supplier's resilience level based on the fulfillment rate, Equation 4.1 demonstrates how to compute it.

    (d) Third, we used Supply chain operation reference (SCOR) as managerial methods to conclude on using Key performance Indicators such as reliability, responsiveness, and agility on the supplier features data. We then integrate both methods to produce the probability of disruption occurrence of supplier which is obtained using the Equation 4.2probabilistic risk assessment. Where R is risk, P is probability of occurrence disruption, and I is the impact which we apply resilience level due to the unavailability of financial effectiveness of supplier data.

(e) Sixth, at this point, the results database will have all of the reports from the suppliers who have been analyzed. As a result, when accepting a new supplier, RSSS will first check to see if the supplier analysis already exists in this database.

2. Dynamic stages: As illustrated in Figure4.1, the dynamic stages of RSSS contains two stages machine learning techniques and results analysis where the system validate the results. The following demonstrate the dynamic stages in detail:

   (a) Fourth, RSSS enter a dynamic stage, during which we train the machine learning algorithm on our data and subsequently model it using appropriate regression algorithms such as: Logistic Regression (LR), Support Vector Machine (SVM), and Random Forest (RF) that are offered through an open source machine learning libraries Pandas, Scikit-learn[94] This stage contain three main steps as follows:

      i. Training: In this step the machine learning model is provided with training data to learn about the suppliers. Therefore, RSSS is trained on suppliers as resilient or not.

      ii. Modeling: After the training step of the machine learning model, mathematical representations are calculated before the inspected suppliers are leveled.

iii. Supplier Resiliency Level: The system is ready to generate a resiliency level for every supplier. The generated resiliency level indicates whether supplier resilient or not.

(b) Fifth, in this stage, RSSS validates the results to determine if the supplier is resilient, which indicates a low risk on its process of supplying the manufacturer, or not resilient, which indicates a high risk on its process of supplying the manufacturer, respectively. Validation is carried out utilizing the median square error, the root mean square error, and the R2 score. As the last phase of this stage, the system reports to the manufacturer the level of supplier resilience and provides a detailed explanation of a supplier weakness.

4.2.3 Operational Implementation

Many firms have taken steps to cut down on the number of suppliers they use. There may be a limit to how far this process should go. When only one supplier takes care of a single item or service, it can be suitable for cost and quality management, but it can be risky in terms of how well single supplier can keep up the item or service. Even though it might be good to have a lead supplier, other sources should be available. When a business has a lot of different locations, it may be possible to get an item or service from the same source for each one. This way, the business can get some of the benefits of single-sourcing without worrying about the risks. If a manufacturing company makes a lot of different things, it might be possible to only get supplies for a few of them, but it is essential to have a backup source if things go wrong.

One of the most important things to look for when choosing a supplier is the supplier's risk awareness. For example, have they looked at their supply chain to see risks? The questions are: Do they have risk-monitoring and risk-mitigation practices in place? It might be good for the manufacturer to work closely with their essential suppliers to improve their supply chain risk management processes. Here RSSS came advantageous to the manufacturer and kept the resiliency level of their suppliers high, utilizing the individual report for each supplier that was restored in the database and ready for the manufacturing decision-maker to decide the following:

1. Continue requesting from specific suppliers.
2. Discontinue requesting from specific suppliers.
3. Is investing in certain suppliers worthy or not?
4. Why is this supplier being risky to supply?
5. How can the manufacturer improve that supplier process?

Factual data will support all the decisions regarding supplier behavior. Since the RSSS indicates the strength and weakness of every analyzed supplier.

4.2.4 Generating Risk Level

We used Supply chain operation reference (SCOR) as a management method to arrive at a risk level based on supplier features data such as reliability, responsiveness, and agility. Then, we used swing weighting method based on delivery lead time, capability, and agility then produce the probability of a disruption supplier occurring based on the static resiliency level. After that, we integrated all methods into the dynamic supervised machine learning algorithms. An illustration of all mentioned methods are as follows:

1. SCOR Performance Method: Supply Chain Council (SCC) established the Supply chain operation reference (SCOR) model in 1996, and it has shown to be a very effective tool in the decision-making process for supply chain strategic decisions. Through the provision of a comprehensive collection of process details, performance measurements, and industry best practices, it enables companies to

conduct a very detailed fact-based study of all parts of their supply chain. The Key Performance Indicators (KPIs) for suppliers developed from the SCOR performance measurements allow us to evaluate different suppliers from the perspective of a manufacturer and assess the risk associated with each of those providers. It is determined which measures of the SCOR performance are most important to measure and which metrics should be aggregated using a value based approach to multi-criteria decision making. A value function based on the most essential metrics is constructed and used to alter the SCOR measures for reliability, responsiveness, and agility, as well as for asset management efficiency; in order to improve. Using the value function, you can combine all of the qualities into one single measure of effectiveness. In order to establish trade-offs between the cost and effectiveness of providers, the cost of the supplier is separated from the effectiveness metric. Due to the fact that some of the SCOR metrics are concerned with assessing activities for material flow, the suggested model is targeted for use in manufacturing supply chains.

- Reliability: The capacity to accomplish duties as expected is referred to as dependability. This characteristic is concerned with anticipating the result of a procedure. Perfect order fulfillment is the level-1 measure linked with dependability, and it may be defined as the proportion of orders that fulfill delivery performance requirements with complete and correct paperwork and no delivery damage. Perfect order fulfillment is further subdivided into the following categories: the proportion of orders delivered in full, the performance of deliveries to client commitment dates, the correctness of paperwork, and the condition of the order.

- Responsiveness: The responsiveness of a supply chain refers to the speed with which jobs are completed in the supply chain. Customers' orders are fulfilled in an average of three business days, which is indicated by the order fulfillment cycle time. The order fulfillment cycle time (OCT) is made up of the cycle times for the source, manufacture, delivery, and retail delivery.
- Agility: The capacity of a supply chain to adapt to changes in the marketplace in order to obtain or preserve a competitive advantage is described as agility.

2. Swing Weighting: It is possible to set the weights in an additive multi attribute utility function using a method known as swing weighting. It is assumed that the lowest utility score on each characteristic is 0 and that the highest utility score is 1. This is known as the swing weighting. we use swing weighting method based on delivery lead time DLT, capability C, and agility A as equation4.3 compute that.

$$(SW) = 100X(DLTX0.55) + (CX0.25) + (AX0.20) \tag{4.3}$$

3. Probabilistic Risk Assessment: A lack of effective risk quantification causes many projects to fail to finish within their initial cost and time projections. Identifying risks and evaluating them in order to provide data that can be used to determine how to respond to matching risks is known as risk quantification. The identification of risk is the first step toward quantification of risk. Once a risk has been identified, it must be evaluated in terms of its probability of occurring and the potential impact it may have on the result. Equation of probabilistic risk assessment found as Equation4.2

4.3 Machine Learning Techniques

As seen in Figure 4.2, machine learning is a multidisciplinary field of study that integrates concepts from several fields of science, including artificial intelligence, information theory, and mathematics. Machine learning is the process of programming computers to maximize a performance criterion based on previous data or experience. We have a model defined up to a certain number of parameters; learning is the process of executing a computer program to optimize the model's parameters using training data or prior experience. The model may be predictive in nature in order to make future predictions, descriptive in nature in order to gather information from data, or both. Machine learning research is primarily focused on the creation of efficient learning algorithms capable of making predictions about data. Machine learning is also a technique used to develop predictive models for data analytics. Machine learning is classified into three categories: supervised, unsupervised, and reinforcement learning. Supervised machine learning involves training on labeled data [8]. For the labeled training data, it integrates input data with a desired target output data to produce the labeled training data. The algorithm for supervised learning analyzes the training data and generates an inferred function that can be used to map new values. Unsupervised machine learning techniques, such as cluster analysis, extract hidden insights from unlabeled data sets. The third category, reinforcement learning, enables a machine to learn its behavior through interactions with its external environment[98].

When developing supervised algorithms, the goal is to locate the best hypothesis space that separates classes that are capable of making accurate predictions for a particular problem. Finding the best theory, on the other hand, is difficult. Because of this, researchers devised a strategy that seeks to produce a better hypothesis than the best hypothesis on its own. A supervised learning algorithm that provides better performance accuracy can be constructed by constructing a group of learning algorithms. Random Forest and Ada Boosting are two of the most popular ensemble algorithms available.

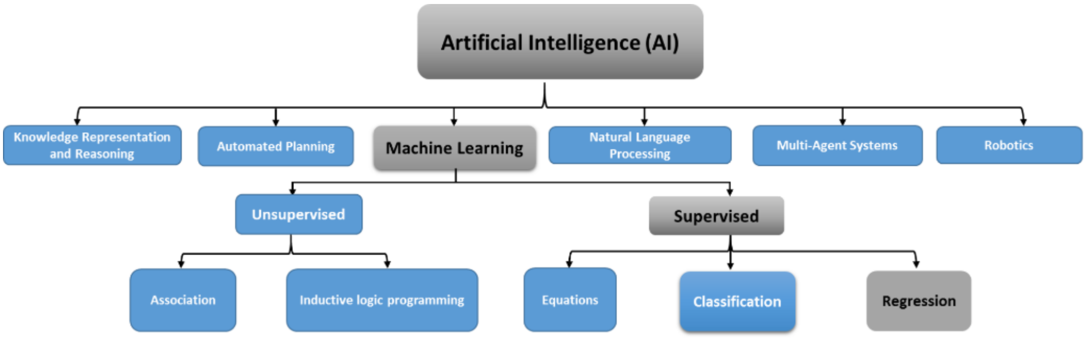

Figure 4.2: Machine Learning Techniques

4.3.1 Random Forest

The Random Forest algorithm is made up of a number of different decision trees. Decision trees are trees that sort samples in a given data set according to the values of their features[67]. Nodes and branches are the building blocks of a decision tree, with each node representing a feature and each branch representing a value that the node is willing to accept. The split of each node is determined by finding the optimal splits across all variables and applying those splits to that node[73]. The classification results of decision trees are represented by the leaf nodes. As previously said, Random Forest is an example of an ensemble algorithm, which mixes a large number of decision trees in order to increase the accuracy of the performance. When using Random Forest, each tree categorizes a set of data that is randomly taken from the input data. A tree is used to categorize and label the results of testing. Once a testing data point has been labeled, which is also referred to as a vote, the forest determines the classification result depending on which trees have received the most number of votes. As a result, the precision of the Random Forest method is dependent on the precision of each individual tree[73]. The Random Forest algorithm works in the following ways:

1. Create n tree bootstrap samples from the original data using the original data.

2. Create a classification tree for each of the n trees you've constructed by using the bootstrap method.

3. Sort new data into categories based on the votes of the majority of the trees.

Figure 4.3 shows the architecture of Random forest.

1. Advantages:

   - Random forest may be used to solve classification and regression issues, and it is quite versatile.
   - A large number of trees are created on a portion of the data, which helps to mitigate the overfitting problem.
   - Random forest may be used to analyze categorical and continuous data, as well as to deal with missing values.
   - There is no need for feature scaling, and the algorithm can handle non-linear parameters.

2. Disadvantages:

   - Take a longer duration of time to train.
   - A higher level of computer power and energy are required because of the algorithm's complexity.

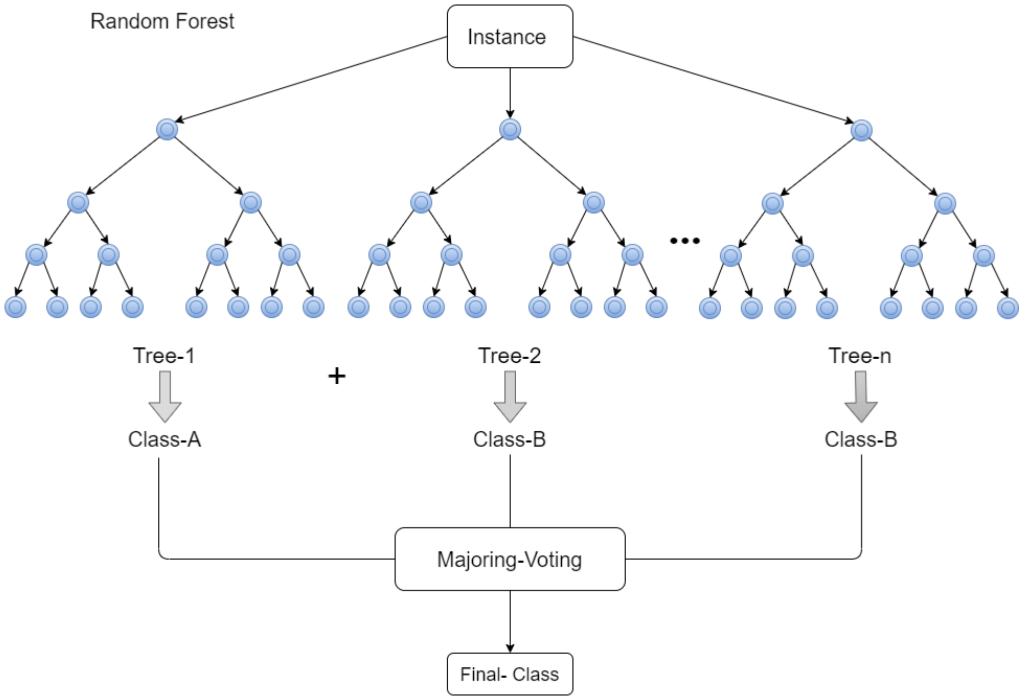

Figure 4.3: Random Forest

4.3.2 AdaBoost

Adaptive Boost Regressors are meta-estimators that begin by fitting a regression model to the initial dataset and then fitting further copies of the regression model to the same dataset, with the weights of instances being changed in accordance with the accuracy of the current prediction. [24]. AdaBoost is known for its efficiency in terms of computing time and memory utilization.

1. Advantages:

   - Working as parallel processing, which explains why it is significantly quicker.
   - Cross-validation is used to handle missing values and to find the optimal number of boosting rounds in a single run, both of which are very useful.

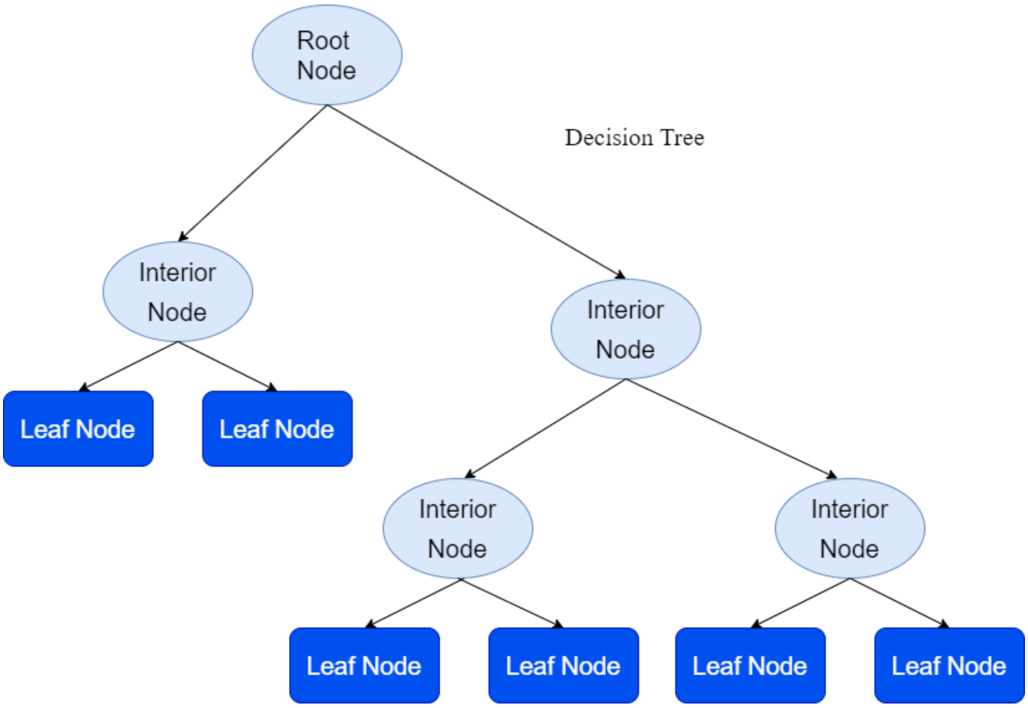

Figure 4.4: Decision Tree

- Ada Boost is a regularization technique that prevents the model from becoming overfitted.

2. Disadvantages:

- It is possible to have overfitting when using the Ada Boost model with incorrect settings.
- Visualization and understanding are both challenging tasks in this case.

4.3.3 Decision Tree

A decision tree as shown in Figure 4.4 is a predictive model that begins with just a single node before branching further into possible outcomes. Each of these outcomes results in other additional nodes which later branch off to form other possibilities giving it a shape that resembles that of a tree. Each node is developed so as to test a given feature before branching out to form a test output where every leaf node is a representation of a given category [15]. Excessive over-fitting is a significant issue in decision tree algorithms. As a result, entropy and information gain must be evaluated when using decision trees. The Equation4.4 demonstrates how to compute it.

$$E(S) = \sum_{x \in X} - p(a)E(a) \tag{4.4}$$

$$Gain(A, S) = E(S) - \sum_{a \in T} - p(a)E(a) \tag{4.5}$$

S denotes a dataset, X denotes a collection of classes included inside S, and p denotes a ratio of the number of entries in class x. The following is the method by which the data gain is calculated: In the Equation 4.5, T represents the subsets that were produced from the dataset S.

1. Advantages:

    - When it comes to data preparation, decision trees save time and effort.
    - The data already normalized before the data step.
    - The data already scaled.
    - Even if there are missing value, the data can still be processed.

2. Disadvantages:

    - When compared to other methods, the computation might be time-consuming.
    - It may take some time for the model to be trained.

- Any alteration to the data can have an influence on the structure of the decision tree, and vice versa.

4.3.4 Logistic Regression

Logistic regression may be compared to the probabilistic model that uses the sigmoid function Equation4.6 to make predictions. The concept of logistic regression is that features are loaded and then each feature is assigned a weight, following which the total of the features is calculated using the sigmoid function to get the final prediction result. Gradient ascent optimization is used to determine the optimal weight to be used. The sigmoid function's input is shown by the Equation4.7 to be x, where W is the weight and X is the set of characteristics. This optimizer requires a significant amount of processing effort, and when modifications are made, they affect the whole dataset each time.

$$S(x) = \frac{1}{1+ \in^{x}} \tag{4.6}$$

$$x = W_0 X_0 + W_1 W_1 + ... + W_n W_n \tag{4.7}$$

1. Advantages

   - It is less difficult to put into action.
   - Trainees are extremely productive.

2. Disadvantages

   - It has the potential to result in overfitting.
   - It has the potential to result in low accuracy.

This experiment was done using pycharm, python language and Excel. The libraries that we used are panada, and sklean. The operating system is Mac OS.

4.4 App Dataset

This dataset is a multivariate, sequential, Time-Series dataset. Data named Purchase material in shoes manufactured in 2020, found in dataset base. The dataset contains 23 columns. The most useful for our experiments are supplier, location, PO date, PO Qty, Invoice date, incoming Qty, PO Y/N, Incoming date and even Incoming date Vs PO date. Dataset holds more than 409000 rows. First, we used 10,000 row followed by 20,000 rows, then 100,000 rows. Dataset contains 482 suppliers. [99].

CHAPTER FIVE

EVALUATION AND RESULTS

This chapter discusses the Evaluation and elaborates the discussion in this research. It also includes the effectiveness of RSSS in terms of analyzing the suppliers that are coming to the RSSS by utilizing machine learning models based on their Mean squared Error (MSE), Root Mean Square Error (RMSE), mean absolute error, and R2-score metrics. Then, it presents and discusses the supplier results, including resiliency level for sample of the suppliers. Then, Justify why this supplier is not resilient by providing a sample of the supplier's report.

5.1 Evaluation

The porpuse for this study is to apply dataset of suppliers that have various items supplying SME manufacturer. Then, analyze their featured data and generate resiliency level and risk level for each supplier. App dataset profile for shoe manufacturer in Indonesia can be applied by researchers to build analyzed database of suppliers with indication of resiliency and risk level of each supplier. The App dataset is described as follows:

- The data was collected by shoe manufacturer in Indonesia and has various supplier for various items from various destination.
- The data has 23 features as shown the used features in the Table 5.1.
- The dataset was made available on the Internet and is open to the public, it may be downloaded in both PCAP and CSV formats.

In our study, we used the app dataset[99] with nine features as. Dataset with nine features include supplier, location, PO date, PO Qty, Invoice date, incoming Qty, PO Y/N, Incoming date and even Incoming date Vs PO date.

Table 5.1 Features used in App Dataset

Feature Name	Feature Description
Supplier	A business that makes a contribution of products or services
location	The supplier location from the manufacturer
PO date	Purchase Order of item data
PO Qty	Number of Purchase Order
Invoice date	The date of invoice
incoming Qty	Total items that received
Incoming date Vs PO date	The difference in days of incoming date and purchase order date

5.1.1 Evaluation Metrics

To evaluate the performance of our machine learning models, an evaluation was used as follows:

- Mean squared Error (MSE): is an absolute measure of how well a model fits the data. MSE is derived by squaring the prediction error, which is equal to the difference between the real and predicted output, and dividing the result by the number of data points. It provides users with an absolute number indicating how far the projected outcomes differ from the actual results. Even while a single result may not provide many insights, it does provide an actual number that can be compared to other model results and used to assist users decide the most appropriate regression model to use. Mean squared error can calculated by using the following equation5.1

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - x_i)^2 \tag{5.1}$$

- Root Mean Square Error(RMSE): The square root of mean square error is known as root mean square error. For example, the MSE number might often be too large to compare readily, hence this method is more usually employed than the MSE value. Second, because MSE is computed as the square of the error, taking the square root of the error returns it to the same level as the prediction error, making it easier to grasp the results. Equation 5.2 is presented the root mean square error formula.

$$RMSE = \sqrt{(\frac{1}{n})\sum_{i=1}^{n}(y_i - x_i)^2} \tag{5.2}$$

- Mean Absolute Error: The Mean Absolute Error (MAE) is a metric that is related to the Mean Square Error (MSE). Instead than using the sum of squares of error as in MSE, MAE uses the sum of the absolute value of error as a measure of error. 5.3:

$$MAE = (\frac{1}{n})\sum_{i=1}^{n}|y_i - x_i| \tag{5.3}$$

- R2-Score: R Square is a measure of how much variability in a dependent variable can be explained by a model, and it is calculated as It is the square of the correlation coefficient(R), which is why it is referred to as R2 Square in mathematics. It can be calculated by using the following equation5.4:

$$R^2 = 1 - \frac{SS_{Regression}}{SS_{Total}} \tag{5.4}$$

R Squared or Adjusted This is a better way to explain the model to other people because user can show the number as a percentage of how much the model changes. Adjusted R square is the only metric here that takes into account over-fitting because of that we neglected it and we used R squared. The best way to compare the performance of different regression models is to use MSE, RMSE, or MAE to figure out which one is the best. RMSE would be better for me, and we think researchers also uses it to look at entries. Because of this, it makes sense to use the MSE if the value is not too big, and the MAE if users don't want to persecute big prediction errors.

5.2 Results

The model and design of the Resilient Supplier selection System (RSSS) were explained in the previous chapter, including implementations. We also illustrated the metrics that are considered in evaluating RSSS. This section presents the results and a discussion of the RSSS. It also demonstrates an evaluation of RSSS by explaining the results of each four experiments. In addition a comparison of all machine learning algorithms evaluation as demonstrated in table5.5

- Experiment 1:

  We generated a sample file that contained 10,000 rows and we balanced the data to earn a strong evaluation. The data file had 241 suppliers. When evaluating the dataset, depending on the resiliency level, each model provided us with different Mean squared Error (MSE), Root Mean Square Error (RMSE), mean absolute error, and R2-score metrics. We began running all 23 features and compared them among others. When we ran the model, the model had the ability to list the important features that would impact the results, which is 9 features. With this dataset, RSSS achieved approximately 97% as R2-score the best evaluation metric. The highest rate was gained by the Random Forest models, as shown in Figures 5.1. The other regression models achieved lowered R2-score, such as Logistics Regression which gained a 88.98% R2-score and almost equally mean squared error, Adaboost Regressor with 64% R2-score, and finally Decission Tree Regressor detected the lowest R2-score with 47%.

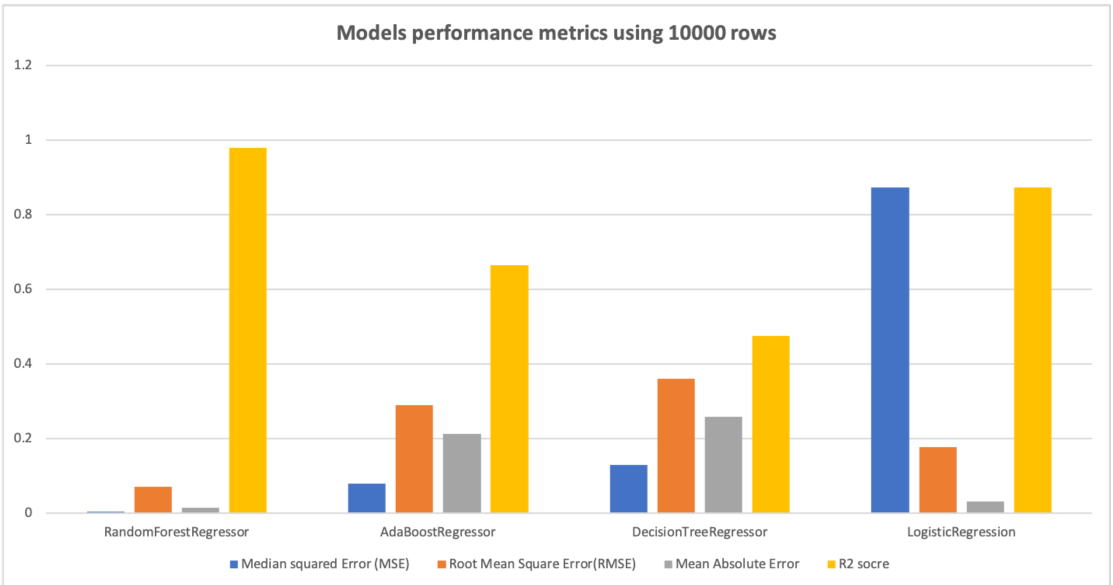

Figure 5.1: Models Performance Metrics in 10,000 Rows

- Experiment 2:

  We generated a sample file that contained 30,000 rows and we balanced the data to earn a strong evaluation. The data file had 311 suppliers. When evaluating the dataset, depending on the resiliency level, each model provided us with different Mean squared Error (MSE), Root Mean Square Error (RMSE), mean absolute error, and R2-score metrics. With this dataset, RSSS achieved approximately 98% as R2-score the best evaluation metric. The highest rate was gained by the Random Forest models, as shown in Figures 5.2. The other regression models achieved lowered R2-score, such as Logistics Regression which gained a 89.65% R2-score and almost equally mean squared error with 89.98%, Adaboost Regressor with 62% R2-score, and finally Decission Tree Regressor detected the lowest R2-score with 48%.

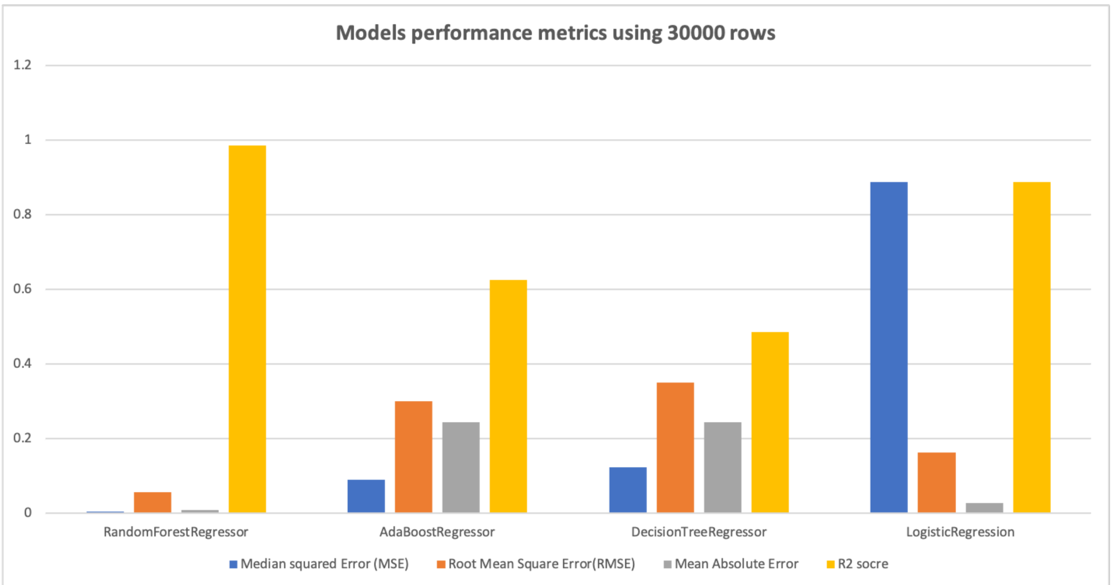

Figure 5.2: Models Performance Metrics in 30,000 Rows

- Experiment 3: We generated a sample file that contained 30,000 rows and we balanced the data to earn a strong evaluation. The data file had 390 suppliers. When evaluating the dataset, depending on the resiliency level, each model provided us with different Mean squared Error (MSE), Root Mean Square Error (RMSE), mean absolute error, and R2-score metrics. With this dataset, RSSS achieved approximately 99% as R2-score the best evaluation metric. The highest rate was gained by the Random Forest models, as shown in Figures 5.3. The other regression models achieved lowered R2-score, such as Logistics Regression which gained a 86% R2-score and almost equally mean squared error with 87%, Adaboost Regressor with 64% R2-score, and finally Decission Tree Regressor detected the lowest R2-score with 44%.

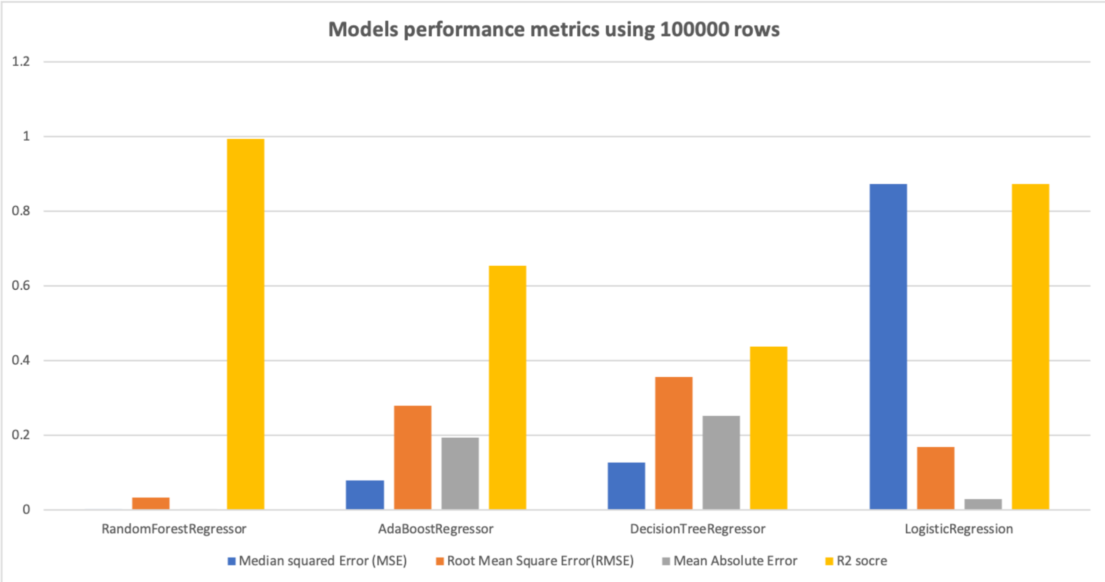

Figure 5.3: Models Performance Metrics in 100,000 Rows

- Experiment 4: We generated a sample file that contained 30,000 rows and we balanced the data to earn a strong evaluation. The data file had all 482 suppliers. When evaluating the dataset, depending on the resiliency level, each model provided us with different Mean squared Error (MSE), Root Mean Square Error (RMSE), mean absolute error, and R2-score metrics. With this dataset, RSSS achieved approximately 99.90% as R2-score the best evaluation metric. The highest rate was gained by the Random Forest models, as shown in Figures 5.4. The other regression models achieved lowered R2-score, such as Logistics Regression which gained a 88% R2-score and almost equally mean squared error with 87%, Adaboost Regressor with 56% R2-score, and finally Decission Tree Regressor detected the lowest R2-score with 42%.

The similar models were utilized in Experiment 1, 2, and 3 utilizing the feature selection approach [76], despite the fact that the model used in Experiment 4 had favorable

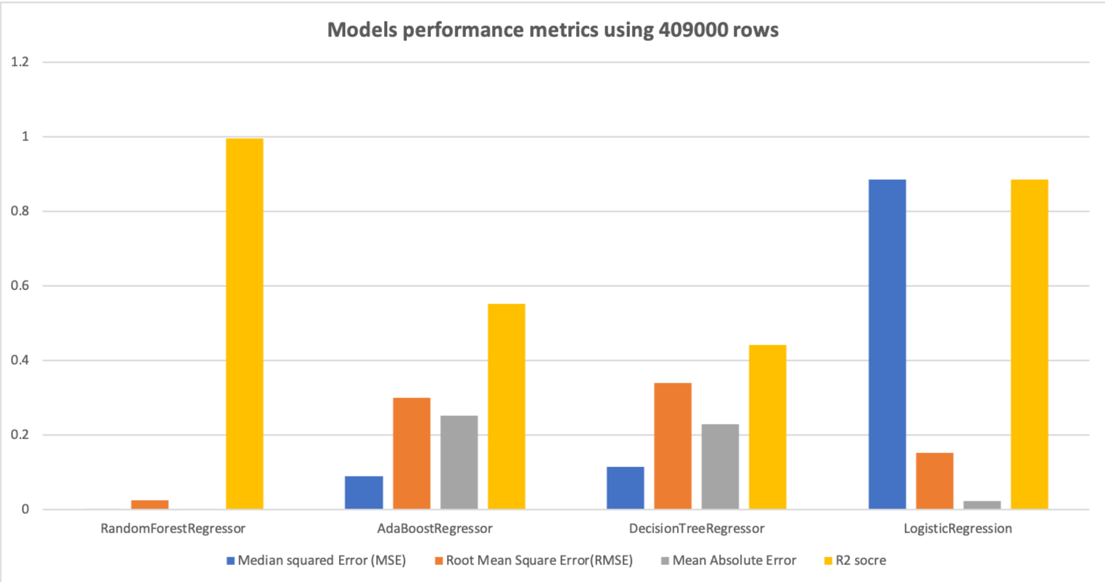

Figure 5.4: Models Performance Metrics in 400,000 Rows

Table 5.2 Comparison of all algorithms App dataset- Experiment 1

Metrics	**Random Forest**	**AdaBoost**	**Decision tree**	**Logistic Regression**
Experiment 1				
MSE (%)	0.0002	0.0768	0.1405	0.8705
RMSE (%)	0.6053	0.2501	0.3807	0.1789
MAE (%)	0.0024	0.2109	0.2433	0.0385
R2-Score (%)	0.9735	0.6447	0.4767	0.8889

Table 5.3 Comparison of all algorithms App dataset- Experiment 2

Metrics	**Random Forest**	**AdaBoost**	**Decision tree**	**Logistic Regression**
Experiment 2				
MSE (%)	0.0010	0.1135	0.1680	0.8703
RMSE (%)	0.0591	0.3006	0.3680	0.0379
MAE (%)	0.9565	0.9565	0.9533	0.9685
R2-Score (%)	0.9967	0.6467	0.4462	0.8689

Table 5.4 Comparison of all algorithms App dataset- Experiment 3

Metrics	**Random Forest**	**AdaBoost**	**Decision tree**	**Logistic Regression**
Experiment 3				
MSE (%)	0.0006	0.0889	0.1207	0.8703
RMSE (%)	0.0291	0.2786	0.3883	0.1890
MAE (%)	0.0002	0.1903	0.2565	0.0332
R2-Score (%)	0.9967	0.6467	0.4462	0.8689

Table 5.5 Comparison of all algorithms App dataset- Experiment 4

Metrics	**Random Forest**	**AdaBoost**	**Decision tree**	**Logistic Regression**
Experiment 4				
MSE (%)	0.0001	0.0895	0.1034	0.8704
RMSE (%)	0.0243	0.3407	0.3759	0.1703
MAE (%)	0.0002	0.2408	0.2265	0.0290
R2-Score (%)	0.9989	0.5667	0.4289	0.8832

Table 5.6 Important features by Regression Models

Important features
Supplier
Location
Inv Date
Material Name
Unit
PO date
PO Qty
Invoice date
Incoming Qty
PO Y/N
Incoming date
Incoming date Vs PO date

results. Feature selection is a technique for reducing the amount of characteristics utilized in the construction of a predictive model [17]. Using feature priority to pick excellent features for machine learning is a relatively simple, rapid, and typically accurate method of selecting best features for machine learning [81]. As a result, each method may provide various important features depending on the type of dataset used as illustrated in Table5.6

5.2.1 Results of Resiliency level

In this section, we discuss a sample picked randomly from the database of six suppliers' resiliency and risk level analyzed by RSSS and stored in the database as demonstrated in the table5.7. The table showed the resiliency and risk levels, resiliency prediction, and probability of disruption occurrence for the pointed suppliers. We measure the resilience supplier based on all 9 features we motioned earlier in table5.1 in addition we done sewing weighting based on delivery lead time, capability, and agility to obtain

Table 5.7 Random 6 Supplier' Resiliency And Risk Levels

	Resiliency Level	Resiliency Prediction	Risk Level	Probability of Disruption
Supplier1	Resilient	85%	Low Risk	35/100
Supplier 36	Not Resilient	53%	High Risk	70/100
Supplier 64	Not Resilient	49%	High Risk	90/100
Supplier 93	Resilient	95%	Low Risk	15/100
Supplier 249	Not Resilient	75%	High Risk	75/100
Supplier 390	Not Resilient	49%	High Risk	70/100

probability of disruption occurred. Therefore, all this mathematical processes and features involved to conclude the resiliency prediction that based on the risk level too. For that, we can see high resiliency prediction but not resilient supplier since it has higher probability of disruption and high risk as Supplier 249 from the table5.7. While the other suppliers, show normality on the term of resiliency and risk level and probability of disruption occurrence.

5.2.2 Related Work Comparison

Previous approaches to identify resilient supplier selection currently exist. Such approaches, however, have only been employed and evaluated for one layer of forecasting disruptive suppliers and they either ignore the risk profile for supplier or build their results based on theoretical facts. Therefore, these approaches were not designed to consider the building and analyzing the risk profiles of selected suppliers. furthermore, computational capabilities of smart manufacturing historical data has not been utilize properly. Table5.8 demonstrate the closest work comparison based in four main outcomes for each supplier; resiliency level, risk level, dataset of suppliers analyzed, and probability of disruption occurrence.

Cavalcantea et al.[21] is the most related work to RSSS and presented hybrid technique to build combines simulation with machine learning and to investigate its potential applications in data-driven decision-making support for resilient supplier selection. additionally consider on-time delivery as a sign of supplier reliability, and investigate the circumstances influencing the establishment of resilient supply performance performance profiles. The theories of risk profile of supplier performance and resilient supply chain performance are then theorized by the researchers. They have demonstrated that their technique is effective in understanding the relationships between deviations from the robust supply chain performance profile and the risk profiles of supplier performance. In conclusion, the findings imply that, when appropriately used, a combination of supervised machine learning and simulation can increase the reliability of delivery.

Ravindran et al. [103] They tackle the risk-adjusted supplier selection problem in two phases as a multi-criteria optimization problem. Various multi-objective ranking algorithms are used to limit a big number of initial suppliers to a smaller number of controlled vendors or suppliers in Phase 1. Using a multi-objective optimization model, order amounts are allocated among the vendors shortlisted in Phase 2. To get the best overall outcome, price, lead time, VaR-variance-covariance risk of interruption due to natural catastrophe, and MtT risk of quality are expressly treated as competing objectives. They also use four alternative goal programming techniques to solve the multi-objective optimization problem. The models are presented using a real-world application for a global IT business.

Alikhani et al. [4] They have established a paradigm that considers both risk-averse and risk-neutral approaches to the selection problem. They employ a non-parametric mathematical programming approach called super-efficiency DEA (Data Envelopment Analysis) to choose the best provider from a pool of applicants. Using a real-world supermarket chain in Iran, they exhibited a multi-method strategy. Using their

Table 5.8 Comparison of method between the proposed RSSS and close work

Studies / Features	Resiliency Level	Risk Level	Dataset	Probability of Disruption
Cavalcantea et al. [21]	✓	×	✓	✓
Ravindran et al. [103]	×	✓	✓	✓
Alikhani et al. [4]	×	✓	×	×
Rajesh and Ravi [100]	✓	✓	×	×
RSSS	✓	✓	✓	✓

quantification approach and the DEA model, decision makers may make reasonable and objective judgments despite the fact that most real-world situations are subjective. Achieving sustainability requirements and risk factors individually rather than concurrently has a favorable influence on the selection process, according to their results. Risk factors examined using qualitative data (DMs' intuitive assessment). However, if risk measurements are based on objective historical data, the conclusions will be more reliable.

Rajesh and Ravi [100] A resilient supplier is one selected as part of a resilient supply chain. Consider an electronic supply chain with six providers. This study calculated grey possibility values for supplier selection and then ranked the suppliers. A sensitivity study was also performed to see how the weightings provided to each of the resilience attributes affect the supplier selection priority.

CHAPTER SIX

CONCLUSION

6.1 Summary of Contributions

This study was conducted to assess current supplier frequently whether they are resilient or not, then build a risk profile for each supplier. The substantial contributions of this research with respect of building the risk profile for each are summarized below:

1. To gather and store all related data in one place (suppliers database) for each supplier for decision makers and future improvement.
2. To reduce the disturbance for suppliers by understanding their behavior.
3. Supplier behavior can be trained, studied, and predicted by the time.
4. Predict the resiliency level of each supplier
5. Generate the risk level of each supplier.
6. Calculate the probability of disruption occurrence of each supplier.
7. Decision maker can decide clearly when the visibility is high on each supplier, whether they continue with/or discontinue or invest on them to improve.
8. The whole supply chain will be more resilient and capable.
9. The manufacturers will improve their reliance on their suppliers.
10. Reporting the manufacturer and restoring in a database the analyzed suppliers.
11. Suppliers' weaknesses and strengths are present in the supplier report.

6.2 Conclusion

Every supply chain organization has a number of severe production challenges, one of which is the inability to forecast the behavior of suppliers. Ability to anticipate how many units of each item a manufacturer will produce in a given month would help the manufacturer to better manage demand. Additionally, projections from suppliers can assist in directing production efforts in the right direction, boosting the possibility of establishing a resilient supply chain. When it comes to established providers, machine learning is employed as a regression tool. The resilient supplier selection system (RSSS) was designed with the goal of mitigating supplier risk and determining the resilience level of a supplier for small and medium-sized enterprises (SMEs). As a result, RSSS is composed of two primary processes: static and dynamic. Static procedures are lightweight conditions that run on every supplier's data in order to study the supplier and provide a resilience level based on the features and fulfillment rates that are currently accessible to the supplier. Then, utilizing the SCOR technique and its key performance indicators (KPIs), swing weighting, and probabilistic risk assessment, the static process RSSS provides a risk level. Secondly, supervised machine learning algorithms are used to integrate the risk level of a supplier's findings with the supplier's resilience level, after which the results are validated and the manufacturer is reported before the results are stored directly into a database. Our RSSS was useful to the manufacturer because it allowed them to maintain a high degree of supplier resilience by employing specific reports for each supplier that were restored in the database and made available for production decision-makers to use as following:

- Continue to request products from specific suppliers.
- Discontinue seeking products from specific suppliers.
- Is it worthwhile to invest in specific suppliers or not?

- What is it about this company that makes them a risky supplier to work with?
- What can the company do to enhance the supplier process?

All decisions effecting supplier behavior will be based on factual data collected and analyzed. Because the RSSS identifies the strengths and weaknesses of each supplier under consideration.

6.3 Future Work

Our future work will use another real dataset to validate the system in general. This dataset will use different features which will help train the system. The operational implementation will be applied for a Saudi Arabian manufacturer to articulate the results on practical steps. This study can be applied using the same methodology to enhance the industry 4.0 of manufacturers.

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