DECISION SUPPORT SYSTEM FOR RESILIENCE-SUSTAINABLE SUPPLIER SELECTION USING MACHINE LEARNING

by

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To everyone who has been part of my journey, your support, encouragement, and kindness have meant more than words can express. I dedicate this work to you with heartfelt gratitude.

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ABSTRACT

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Global supply chains have become increasingly interconnected and data-intensive, but recent disruptions have shown that traditional supplier selection approaches, often focused on cost, quality, and delivery, are insufficient for ensuring continuity and responsible sourcing. Small and medium-sized enterprises (SMEs) are especially vulnerable because they typically lack the analytical capacity to evaluate suppliers using both resilience and sustainability criteria. This study develops and evaluates a machine learning based decision support system, the Resilient-Sustainable Supplier Selection System (RSSSS), to support data-driven supplier classification and risk-aware sourcing decisions.

The proposed RSSSS integrates operational performance indicators with resilience attributes (e.g., reliability, agility, and geographic diversification) and sustainability-related indicators within a unified evaluation framework. A historical supplier dataset containing 74,339 records and 13 predictive features was preprocessed through data cleaning, categorical encoding, and handling of missing values. Seven supervised machine learning models—Decision Tree, Random Forest, AdaBoost, Naive Bayes, k-Nearest Neighbors, Linear Discriminant Analysis, and XGBoost—were trained and evaluated using accuracy and computational training time.

Results show that XGBoost achieved the highest classification accuracy (82.23%), outperforming all alternative models, while requiring 5.96 seconds of training time. The findings confirm that tree-based ensemble learning can effectively capture complex, non-linear relationships among resilience and sustainability indicators, enabling more accurate identification of resilient-sustainable suppliers than traditional rule-based or static scoring methods. Overall, the RSSSS demonstrates a practical and lightweight approach for SMEs to improve supplier selection speed, transparency, and comprehensiveness, supporting more resilient, sustainable, and risk-aware sourcing decisions under uncertainty.

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SCM	Supply Chain Management
RSSSS	Resilient-Sustainable Supplier Selection System
SMEs	Small and Medium-sized Enterprises
MCDM	Multi-Criteria Decision Making
SCOR	Supply Chain Operations Reference
KPI	Key Performance Indicators
TBL	Triple Bottom Line (Economic, Environmental, Social)
AI	Artificial Intelligence
IoT	Internet of Things
LSTM	Long Short-Term Memory
DSS	Decision Support System
BWM	Best Worst Method
SVM	Support Vector Machines
ML	Machine Learning
ESG	Environmental, Social and Governance

CHAPTER ONE

INTRODUCTION

Overview

Any supply chain in today's globalized economy is part of a highly interconnected network spanning continents, suppliers, and diverse stakeholders. While this interdependence has enabled efficiency and cost optimization, it has also increased the vulnerability of supply chains to disruption. The COVID-19 pandemic, the Russia-Ukraine war, trade tensions between major economies, and climate-related disasters have all exposed the weaknesses of traditional, efficiency-focused sourcing models. In particular, the pandemic has prompted organizations to rethink their approaches to risk management and business continuity, showing that cost-based supplier selection alone is not sufficient to ensure long-term survival [1]. As a result, there is a growing consensus in both academia and industry that supplier selection should go beyond cost and quality criteria to include dimensions of resilience and sustainability, which together shape a firm's ability to withstand, adapt to, and recover from adverse events.

Resilience in supply chain management refers to the ability of the system to anticipate, absorb, and recover from disruptions without significant loss of performance. It depends on different forms of flexibility, redundancy, and visibility across the entire supply chain. Sustainability, on the other hand, focuses on reducing environmental and social harm while maintaining economic viability [2] .

In the past, resilience and sustainability were often treated as separate, or even conflicting, objectives. However, recent studies show that these two dimensions can be mutually reinforcing. A resilient supplier is often one that adopts sustainable practices, such as improving resource efficiency, ensuring fair and ethical labor conditions, and maintaining transparent operations. These practices help reduce environmental impact and operational risks, thereby supporting both long-term resilience and sustainability [3]. Therefore, considering these dimensions is no longer optional; it has become a prerequisite for remaining competitive, complying with regulatory requirements, and meeting stakeholders' expectations regarding the ethical and responsible conduct of business.

Supplier selection, which was traditionally viewed as an operational procurement function, has evolved into a strategic determinant of organizational resilience and sustainability performance. Suppliers are key actors in global value networks and therefore influence a firm's exposure to geopolitical, environmental, and reputational risks. Selecting suppliers with strong risk-management systems, diversified sourcing channels, and well-developed sustainability strategies can significantly enhance the overall resilience of the supply chain [4]. However, these decisions have become more complex due to the large volume and heterogeneity of information that decision-makers must evaluate. Today's procurement managers need to assess not only traditional performance indicators (such as cost, quality, and lead time), but also more complex and unstructured information, including environmental, social and governance (ESG) disclosures and even social media sentiment related to supplier reputation.

With the advent of digital transformation in supply chain management, both the opportunities and challenges associated with supplier evaluation have increased. On the one hand, technologies such as the Internet of Things (IoT), blockchain, and big data analytics enable organizations to generate real-time data on supplier performance. On the other hand, the volume, speed, and complexity of this data exceed the information-processing and analytical capabilities of traditional decision-making models. Conventional multi-criteria decision-making (MCDM) approaches, although effective for small-scale and relatively stable problems, are not well suited to dynamic, uncertain, and high-dimensional data environments [5]. This creates an urgent need for smart, adaptive decision support systems that can process complex data, learn from evolving patterns, and provide evidence-based supplier selection, especially under conditions of uncertainty.

In this context, machine learning (ML), as a branch of artificial intelligence (AI), offers significant transformative potential. By learning from historical data and uncovering latent patterns, ML algorithms can be used to predict supplier performance, classify suppliers according to resilience and sustainability indicators, and reveal hidden risk factors that human decision-makers might overlook [6]. For example, supervised learning methods can predict supplier disruption events using past delivery records, while unsupervised learning techniques can group suppliers based on their level of sustainability maturity. In addition, natural language processing (NLP) can analyze textual data from sustainability reports, media coverage, and financial disclosures to identify signs of potential non-compliance or reputational risk [7].

When these capabilities are integrated into a decision support system (DSS), they enable a shift from reactive to proactive supplier management. Instead of relying on static, retrospective assessments, organizations can conduct predictive analyses of resilience and sustainability to support more timely, informed, and robust supplier selection decisions [8]. The objective of this research is therefore to design a machine learning-based decision support system that enables organizations to make informed, data-driven supplier selection decisions aligned with both sustainability and resilience goals.

The proposed DSS is conceived as a socio-technical artefact rather than a purely technical tool, acknowledging the interdependence between data analytics, procurement policies, and risk management practices. Its main function is to provide decision-makers with an interpretable and transparent set of recommendations that balance operational efficiency with ethical and responsible conduct. The DSS is designed to be integrated into existing supply chain management frameworks, using digital technologies to support decisions that generate not only economic benefits but also environmental sustainability and social well-being [9].

In recent years, global trade has become more uncertain and less transparent, while pressure on businesses to act responsibly has continued to increase. As a result, supplier selection has become a highly complex decision problem that requires advanced analytical support. Using machine learning to evaluate suppliers can help reduce this complexity, but it also raises important concerns related to data ownership, model transparency, and the need to balance algorithmic efficiency with ethical decision-making

[10]. The main purpose of this dissertation is to address these concerns by developing a decision support system that can process complex supplier data, produce forecasts, and risk analyses, and guide organizations towards sustainable and resilient sourcing decisions under conditions of uncertainty.

Background: Supply Chain Complexity and Fragility in the 21st Century

Over the past three decades, global supply chains have evolved from relatively linear structures into complex, multi-tier networks involving thousands of firms distributed across different regions and continents. Advances in logistics, digitalization, and trade liberalization have enabled just-in-time manufacturing and global sourcing, allowing organizations to optimize operations and reduce costs within shorter time frames. However, this strong focus on efficiency has often come at the expense of robustness and resilience, a trade-off that has been increasingly highlighted in recent studies [11].

These supply chains were severely tested by the COVID-19 crisis. Lockdowns, border closures, and factory shutdowns caused major disruptions, leading to significant imbalances in critical sectors, such as semiconductors and pharmaceuticals [12]. This crisis brought resilience back into focus as a key design criterion in supply chain strategies. In addition to the pandemic-related shock, several structural issues in global trade and production systems continue to increase the fragility of supply chains.

Geopolitical developments, such as the Russia-Ukraine conflict, the US-China trade war, and political instability in oil-producing regions of the Middle East, have disrupted traditional trade patterns and forced companies to reassess the political risks associated with specific locations. At the same time, climate change has created a new category of systemic risk. Increasingly frequent extreme weather events, rising sea levels, and volatile commodity prices are having a growing negative impact on transportation, agriculture, and manufacturing activities [13]. When combined with inflation, energy price fluctuations, and exchange rate instability, these uncertainties are redefining global production systems and pushing firms toward regionalization, nearshoring, and more diversified supplier portfolios [14] .

Digital developments add another layer of complexity to this picture. Technologies such as IoT-based monitoring, blockchain-enabled traceability, and AI-driven analytics often grouped under the concept of Industry 4.0 are greatly increasing the volume and detail of data generated across supply networks. While this digitalization has improved the speed, visibility, and accuracy of supply chain operations, it has also introduced new risks related to cybersecurity, data integrity, and technological interoperability [15].

Therefore, modern supply chains must be designed to manage a combination of physical, cyber, and informational risks that can spread in real time across the entire system. These risks are illustrated in Figure 1, entitled “The Evolving Landscape of Global Supply Disruptions.” The figure shows how geopolitics, pandemics, economic shocks, and other disruptive forces converge at the global supply chain nexus. By highlighting the interconnected nature of these disruptions, the figure serves as a reminder that such shocks do not occur in isolation; rather, they interact and amplify one another. This visual representation provides a sobering insight into how ongoing turbulence may severely undermine supplier responsiveness in the long term.

Figure 1 *The Changing Landscape of World Supply Chain Calamities*

Figure 1 illustrates the multiple, intersecting forces that shape global supply chains, including geopolitical instability, climate-induced hazards, pandemics, and economic shocks, all converging on a central global supply chain framework. The graphic highlights how the combined impact of these multidimensional pressures generates increasing levels of complexity and vulnerability within modern supply chains [13].

In conclusion, the modern supply chain environment is highly interdependent and characterized by significant uncertainty. Firms can no longer rely solely on efficiency-oriented models or static risk assessments. Instead, they must develop adaptive mechanisms that strengthen resilience and ensure continuity of operations in the face of ongoing disruptions [16].

Building on this understanding, the next section develops the conceptual foundation for examining resilience and sustainability as the two key pillars of a future-proof supply chain in the contemporary global context.

Resilience and Sustainability: The Definitions and Convergence

Resilience and sustainability have emerged as a dual imperative shaping the evolution of supply chain management in the twenty-first century. Although they were historically treated as separate constructs—resilience associated more with short-term responsiveness, and sustainability with long-term ecological and social responsibility—recent research shows that they are closely interrelated [17]. Both aim to create systems that can endure and perform under changing conditions, but they emphasize different dimensions: resilience focuses on the ability to absorb shocks and recover from disruptions, while sustainability focuses on the ability to operate over the long term without causing environmental or social harm.

As mentioned, supply chain resilience is commonly defined as the ability of a system to anticipate, absorb, and recover from disruptions while maintaining continuity of operations [18]. It is underpinned by four key features: redundancy, agility, visibility, and flexibility.

- **Redundancy**: ensures that alternative suppliers, facilities, or logistics options are available in case of disruption.
- **Agility**: enables rapid adjustments in sourcing, production, or distribution when conditions change.

- **Visibility**: allows firms to monitor risks and performance across the supply chain in real time.
- **Flexibility**: supports the quick reconfiguration of production processes and supply routes.

Together, these capabilities enable resilient supply chains to respond more effectively and emerge stronger after disruptive events. The COVID-19 pandemic and subsequent global crises have shown that firms with resilient supply bases, those able to switch suppliers, reroute shipments, or reorganize production experienced shorter disruption periods and lower revenue losses compared to firms that relied on single, low-cost sourcing models.

Sustainability, in turn, goes beyond operational continuity by addressing the ethical, environmental, and social dimensions of supply chain management. It is grounded in the principles of environmental stewardship, social equity, and economic responsibility, commonly referred to as the triple bottom line. In practice, this means selecting suppliers that comply with environmental standards, respect labor rights, and minimize waste and carbon emissions [19].

Sustainable sourcing is increasingly viewed not only as a moral obligation, but also as a legal and competitive necessity. This shift is reinforced by regulatory frameworks such as ISO 20400:2017 (Sustainable Procurement - Guidance) and emerging mandatory ESG disclosure requirements in the European Union and North America. As a result, companies are paying greater attention to the sustainability performance of their suppliers across the value chain, alongside traditional financial and operational criteria.

Although resilience and sustainability have distinct conceptual roots, they converge on a common goal: ensuring the long-term viability of supply chains in uncertain environments. Resilience is primarily concerned with an organization's ability to absorb, adapt to, and recover from disruptions such as geopolitical conflicts, pandemics, or natural disasters. Sustainability, by contrast, focuses on ethical and regenerative practices that minimize environmental damage and promote responsible governance [20].

The relationship between resilience and sustainability is therefore symbiotic and mutually reinforcing. Sustainable practices, such as reducing resource dependency, improving energy efficiency, and strengthening social responsibility, can enhance resilience by lowering exposure to environmental, social, and regulatory risks. At the same time, resilient supply chains are better positioned to maintain and advance sustainability goals even under conditions of stress and disruption [20].

Having a sustainable supplier base also contributes directly to resilience, because such suppliers typically invest in cleaner technologies, diversify their sourcing channels, and comply with environmental, social, and governance (ESG) standards. These characteristics reduce exposure to resource shortages, legal sanctions, and reputational damage.

Conversely, a resilient supplier base characterized by agile production, flexible sourcing, and high responsiveness supports sustainability by ensuring continuity of operations during crises, thereby maintaining progress towards long-term environmental and social goals [21]. In this way, resilience provides the temporal stability needed for sustainability to flourish, while sustainability strengthens the ethical and environmental foundations that underpin the resilience of the supply chain over time.

However, tensions between these two goals can arise. For example, safety stocks or duplicate suppliers, which are used to build redundancy and enhance resilience, can also generate additional waste and emissions. Similarly, some sustainability initiatives, such as prioritizing local sourcing or low-emission materials, may restrict flexibility and make it harder to respond quickly to disruptions.

As a result, contemporary supply chain management design is increasingly moving toward integrating resilience and sustainability within a single optimization framework. Multi-criteria decision analysis (MCDA) based decision support systems and ML based systems are becoming popular tools for achieving this balance [22]. These systems help decision-makers to manage dynamically changing trade-offs among criteria such as risk exposure, carbon footprint, lead time, and ethical compliance.

Figure 2 *Key Ideas the Supply Chain Resilience vs. Sustainability*

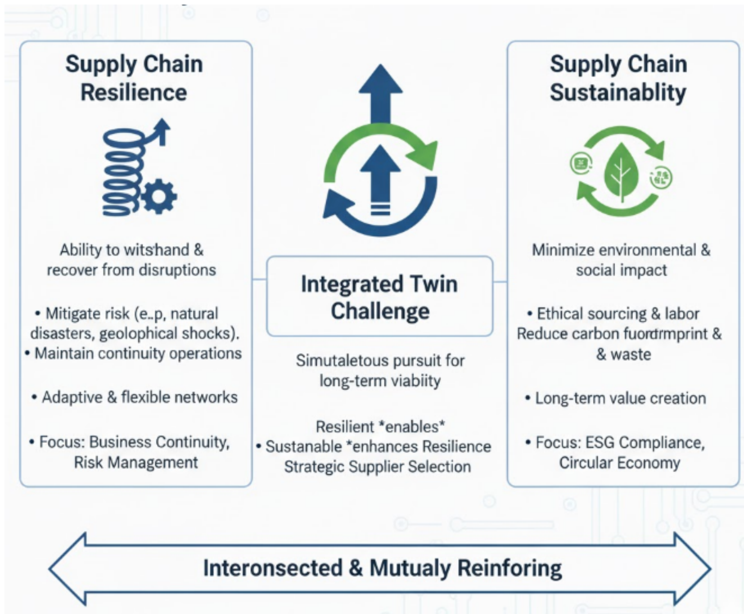


Figure 2, entitled "Core Concepts: Supply Chain Resilience vs. Sustainability," presents a diagrammatic illustration of the relationship between these two paradigms. The model is depicted as two overlapping circles: one representing resilience, characterized by adaptive strength and agility, and the other representing sustainability, associated with ecological balance and ethical responsibility. The overlapping area captures their convergence, showing how transparent, responsible, and socially conscious supplier practices simultaneously enhance systemic resilience and long-term sustainability across the supply chain. Their intersection represents the space where resilient supply chains generate sustainable outcomes, and sustainable practices, in turn, strengthen resilience against disruptions.

In summary, resilience and sustainability are not optional add-ons, but strategic imperatives in global supply chains. Firms that integrate both concepts into their supplier selection processes benefit from improved risk management, stronger regulatory compliance, and enhanced corporate reputation. Accordingly, this dissertation treats resilience and sustainability as complementary dimensions within a unified decision support framework. The research aims to operationalize this integration by developing a system that enables firms to evaluate suppliers intelligently, using data-driven insights that are both adaptive and sustainable in an increasingly volatile global environment.

Supplier Selection as a strategic effort

Choosing a supplier is one of the most strategic decision points in contemporary supply chain management. It goes beyond transactional procurement and has become a key determinant of an organization's operational resilience, cost structure, innovation capacity, and sustainability performance [23]. The complexity of global sourcing has intensified in the wake of the COVID-19 pandemic, the global energy crisis, and the fragmentation of trade networks, all of which have exposed the vulnerabilities created by overly narrow or cost-focused approaches to supplier selection.

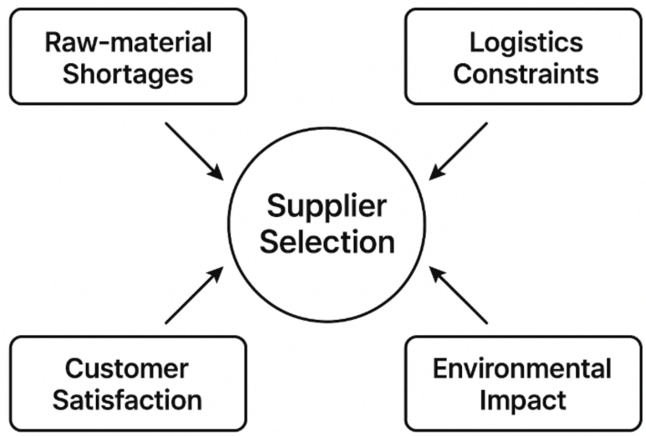
In this context, selecting appropriate suppliers has become a critical factor that can either enhance a firm's ability to withstand shocks or, conversely, threaten its continuity. Suppliers that can recover quickly from disruptions and consistently meet the expectations of diverse stakeholders play a decisive role in securing the overall long-term survival and competitiveness of the firm.

Supplier selection has become a multidimensional optimization problem in modern practice. Traditional evaluation methods, such as weighted scoring and the Analytic Hierarchy Process (AHP), rely on hierarchical comparisons and are therefore limited in their ability to capture the non-linear interdependencies among different evaluation dimensions [24]. Additionally, the proliferation of digital information, such as supplier audit reports, Internet of Things (IoT) data, and ESG disclosures creates a need for data-driven approaches capable of uncovering underlying risk patterns and emerging performance trends [25].

Empirical evidence shows that robust and resilient supplier portfolios enhance overall corporate competitiveness. Firms that include resilience indicators, such as backup capacity, geographical dispersion, and risk-sharing mechanisms, tend to experience shorter recovery times and lower financial losses during disruptions [26]. Likewise, the incorporation of sustainability criteria, such as carbon intensity, labor practices, and waste management, is linked to long-term benefits in terms of regulatory compliance and brand reputation. The main challenge lies in balancing these requirements: resilience often calls for redundancy, while sustainability typically emphasizes efficiency and resource optimization.

To formalize this balance, researchers and practitioners increasingly rely on multi-criteria decision-making (MCDM) and machine learning (ML) models that can capture trade-offs in real time [26]. These systems can be used to forecast supplier reliability using both structured data, such as financial indicators, and unstructured data, such as supplier reports, and social media sentiment.

Figure 3 *The Strategic Role of Supplier Selection in Building Resilient and Sustainable Supply Networks*



As illustrated in Figure 3, supplier selection functions as a central hub within the supply network, where raw material availability, logistics constraints, customer satisfaction, and environmental impact are all interlinked and influenced by upstream risk factors. This central role reinforces the importance of developing intelligent, data-driven approaches to supplier evaluation and selection.

Moreover, the taxonomy of criteria for supplier evaluation has evolved significantly in recent years. Table 1 summarizes the main categories of criteria that are relevant for resilient and sustainable supplier selection in a post-pandemic, data-driven context.

Table 1 *Key Evaluation Criteria in Resilient and Sustainable Supplier Selection*

Category	**Indicative Metrics / Features**	**Strategic Relevance**	**Example Data Sources**
Economic Efficiency	Unit cost, delivery reliability, defect rate	Ensures competitiveness and customer satisfaction	ERP records, performance audits
Resilience	Flexibility, lead-time variability, capacity redundancy, supply diversification	Enhances continuity during disruptions	Supplier risk reports, logistics data
Environmental Sustainability	Carbon footprint, energy use, waste recycling ratio	Aligns with carbon-neutral and circular-economy goals	ESG disclosures, LCA databases
Social Responsibility	Labor practices, community impact, safety records	Supports corporate social-responsibility compliance	CSR reports, certification bodies
Innovation Capability	R&D intensity, technology adoption, digital integration	Promotes adaptability and long-term competitiveness	Patent data, technology indices
Risk Exposure	Political stability, financial solvency, dependency ratio	Identifies systemic and regional vulnerabilities	Financial statements, geopolitical indices
Digital Maturity	Use of IoT, AI, and blockchain in operations	Facilitates transparency and real-time monitoring	Digital-readiness assessments

Table 2 *Evolution from Traditional to Machine-Learning-Enabled Supplier Selection*

Aspect	Traditional Approaches	Machine-Learning-Enabled Approaches	Strategic Advantage
Data Handling	Limited, static datasets	Large-scale, real-time, multi-source data integration	Enhanced decision accuracy
Modeling Technique	Linear scoring or AHP	Non-linear predictive models (SVM, RF, ANN)	Captures complex interactions
Adaptability	Periodic review cycles	Continuous learning and adaptation	Rapid response to disruptions
Transparency	Manual weighting and subjective bias	Explainable-AI frameworks for traceability	Improved governance and trust
Outcome Focus	Cost and quality	Balanced resilience-sustainability trade-off	Strategic alignment with ESG goals

In sum, supply chain resilience and sustainability are fundamentally shaped by supplier selection. The strategic choice of suppliers determines an organization's exposure to risk, its carbon footprint, and its ability to adapt under uncertainty. Decision support systems (DSSs) powered by machine learning, digital twin analytics, and explainable AI have become increasingly necessary in a highly competitive global environment. These technologies enable real-time monitoring of supplier performance and support a proactive approach to supply chain management.

The following section examines how these concepts can be operationalized through machine learning based decision support. The aim is to help bridge the gap between theoretical constructs and practical industrial applications in resilient and sustainable supplier selection.

Data Landscape and Decision Complexity

Supplier selection has become an information-intensive decision-making process, driven by the deep globalization of modern supply chains. Contemporary procurement environments continuously generate, aggregate, and integrate heterogeneous data streams, including transactional records, delivery performance and quality metrics, ESG indicators, financial solvency measures, and real-time sensor data [27]. In addition, external intelligence sources, such as news analytics, social media sentiment, and geopolitical risk indices, complement traditional performance information and form a broader informational ecosystem. The combination of these inputs creates a complex data landscape that decision-makers must synthesize in a way that remains transparent, traceable, and fair, while also complying with increasingly strict sustainability and disclosure requirements.

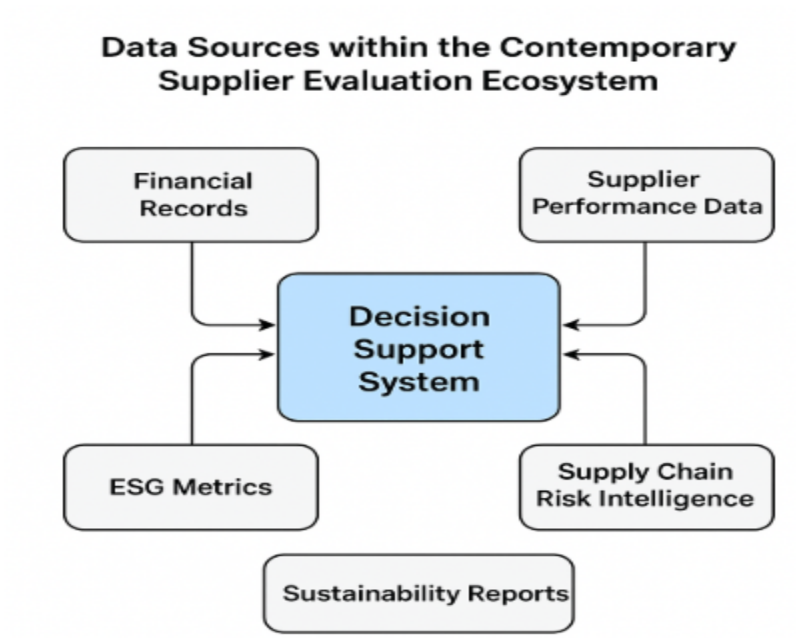
The proliferation of digital technologies and user-generated content has dramatically increased the volume and diversity of information available for supplier evaluation, leading to what is often described as the “5V” challenge of supplier analytics: volume, variety, velocity, veracity, and value. To detect potential disruptions and identify opportunities, procurement systems must be able to process millions of data points across global supplier networks, often in near real time [28].

These data streams include both structured data, such as records stored in enterprise resource planning (ERP) systems, and unstructured data, such as audit reports, textual sustainability disclosures, satellite imagery, and other heterogeneous sources. Velocity is reflected in the continuous flow of updates produced by Internet of Things

(IoT) devices and logistics-tracking systems, which in turn drives the need for low-latency analytical solutions.

However, these advantages are accompanied by new challenges [29]. Veracity issues arise when data are inaccurate, incomplete, or biased, while the “value” dimension concerns the ability to extract actionable insights without being overwhelmed by the noise generated by large data volumes.

Figure 4 *Data Sources within the Contemporary Supplier Evaluation Ecosystem.*



Data Source	Description
Financial Records	Balance sheets, credit ratings, bankruptcy filings
Supplier Performance Data	Delivery times, defect rates, quality scores
ESG Metrics	Carbon emissions, resource usage, labor practices
Supply Chain Risk Intelligence	Geopolitical risk indices, disaster forecasts, supplier risk assessments

In the conceptual model, the outputs of the analytics layer flow into three main decision modules: supplier risk scoring, sustainability assessment, and resilience prediction. The expanding scope and interdependence of supplier-related information make traditional decision models increasingly inadequate, as they typically rely on linear weighting schemes or deterministic scoring. For instance, a supplier's environmental performance may be inversely related to its cost efficiency, while indicators of flexibility may depend on regional risk exposure and the level of technological maturity.

At the same time, emerging regulatory frameworks, such as the European Union's Corporate Sustainability Reporting Directive (CSRD) and climate-related disclosure requirements proposed by the U.S. Securities and Exchange Commission (SEC), are driving demand for supplier evaluation processes that are transparent, explainable, and auditable. In response, firms are increasingly adopting machine learning based decision support systems that can ingest large, heterogeneous datasets and adjust dynamically to uncertainty in the supply environment.

However, the complexity of supplier data extends beyond scale to include semantic and contextual heterogeneity. Sustainability indicators, particularly those based on supplier self-reporting, often lack standardized measurement protocols, while logistics data can vary significantly across carriers, regions, and information systems.

This adds an additional cognitive burden on decision-makers, who must interpret multi-criteria outputs while remaining accountable to ethical, regulatory, and governance standards. As a result, the challenge is shifting from data availability to data interpretability. The ability to explain why a supplier is classified as resilient or sustainable has become just as important as the accuracy or sophistication of the underlying model itself.

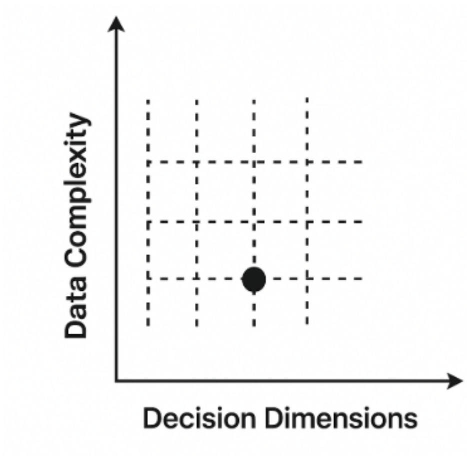
To illustrate the complexity of contemporary supplier data, Table 3 groups the key data types, their sources, associated analytical challenges, and their strategic importance for resilience and sustainability-oriented decision-making.

Table 3 *Categories of Supplier Data and Their Strategic Relevance*

Data Category	**Example Sources**	**Analytical Challenges**	**Strategic Importance**
Operational Performance	ERP records, delivery logs, defect rates	Data inconsistencies, varying KPIs	Benchmarking supplier reliability and efficiency
Financial Health	Balance sheets, credit ratings, bankruptcy filings	Delayed updates, currency fluctuations	Assessing solvency and risk exposure
Environmental Impact (E)	Carbon reports, waste audits, energy-consumption data	Lack of standardization, self-reporting bias	Evaluating compliance with green standards
Social and Governance (S/G)	Labor audits, community impact reports, certification data	Unstructured text, qualitative ambiguity	Ensuring ethical and regulatory conformity
Innovation and Technology	R&D investment, patent filings, digital integration indices	Data sparsity and regional bias	Measuring adaptive capacity and competitiveness
Geopolitical and Climate Risk	Country-risk indices, satellite data, climate models	Spatial heterogeneity, long-term uncertainty	Identifying vulnerability and resilience hot spots
Reputation and Sentiment	News analytics, social media, NGO databases	Noise, misinformation, context dependence	Detecting emerging reputational risks

However, the challenge is not merely to collect data about suppliers, but to transform it into contextualized intelligence. As illustrated in Figure 5, decision complexity arises from the interaction between diverse data types and multiple decision dimensions, economic, environmental, social, and risk related. Under conditions of uncertainty and incomplete information, decision-makers must integrate these dimensions using multi-criteria optimization and predictive analytics in order to derive robust, resilience and sustainability-oriented supplier assessments.

Figure 5 *Data Complexity and Decision Dimensions Intersection point*



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As global supply chains continue to digitize, the volume and diversity of data will only expand, driven by blockchain-based traceability solutions, digital twins, and real-time sustainability monitoring. This evolution necessitates the development of a new generation of decision support systems that not only efficiently process large volumes of data but also ensure transparency, fairness, and explain ability at every stage of the analytics process. These systems represent a paradigm shift from descriptive analytics (what has happened) to prescriptive intelligence (what needs to be done), enabling organizations to dynamically identify, assess, and collaborate with suppliers who contribute to building a more resilient and sustainable supply network.

Machine Learning and Decision Support Systems for Supplier Selection

Machine learning (ML) has transformed decision-making across industries in recent years by enabling systems to learn from data, uncover complex relationships, and generate predictions with minimal human intervention [30]. In supply chain management, supplier selection is increasingly shifting from rule-based decision-making towards data-driven, intelligent approaches. This shift is driven by the exponential growth of supplier-related information, including financial performance, delivery reliability, and quality indicators, as well as sustainability metrics, risk probabilities, and social responsibility ratings [31].

Traditional analytical models often struggle to process such high-dimensional, heterogeneous data. By contrast, ML techniques can leverage modern computational power to detect non-linear relationships among variables and build adaptive models that continuously learn and update as the environment evolves[32]. This makes ML particularly well-suited for supporting robust, dynamic supplier selection in complex and uncertain settings.

A machine learning (ML) enhanced decision support system (DSS) is not a simple automation tool, but a cognitive system that supports managerial decision-making. It combines predictive analytics and optimization models with knowledge-based reasoning to generate evidence-based recommendations [33].

In the context of supplier selection, an ML based DSS can analyze large volumes of data to compare potential suppliers across multiple criteria, including cost, quality, lead time, innovation capability, environmental performance, and resilience, while accounting for uncertainty and changing market conditions[34]. These systems also support scenario analysis (what if analysis), enabling decision-makers to simulate the effects of disruptions, such as raw material shortages, political instability, or carbon taxes, on supplier reliability and sustainability performance.

In addition, supervised learning algorithms such as random forests, gradient boosting machines, and support vector machines (SVMs) can be used to classify suppliers based on their historical performance and to forecast future risk events. Hidden patterns, such as groups of similar suppliers or early warning signals of supplier failure, can be uncovered through unsupervised learning techniques, including clustering and anomaly detection[35]. At the same time, insights from unstructured data, such as supplier reports, ESG disclosures, and social media sentiment, can be extracted using Natural Language Processing (NLP).

By combining these techniques within a DSS, organizations can achieve both high predictive accuracy and greater interpretability. This allows managers to understand the reasoning behind model outputs, which is essential for regulatory compliance and building trust in AI enabled decisions.

The adoption of ML in supplier selection is not without challenges[36]. One of the main concerns is data quality and availability, as supplier-related information often comes from heterogeneous, inconsistent, and sometimes unreliable sources. A further issue is algorithmic bias, where models may unintentionally favor certain types of suppliers if the training data are imbalanced or not representative[37].

Explainability and transparency are also critical, especially when sustainability claims are involved. Risks such as greenwashing, where sustainability performance is exaggerated or misreported, can distort evaluations and lead to misleading decisions. For these reasons, it is essential to design ML frameworks within the DSS architecture that are both robust and interpretable[38]. Such frameworks should support resilience (by enabling adaptation to disruptions) and sustainability (by aligning with ESG standards and ensuring accountable, trustworthy decision-making).

In conclusion, the use of machine learning in supplier selection represents a shift from reactive to proactive, intelligent decision-making within DSS frameworks. By combining ML with multi-criteria decision-making (MCDM) methods such as AHP, TOPSIS, and VIKOR, supplier attributes can first be modelled and weighted using data-driven techniques. Then ranked in a structured and transparent manner[34]. In this thesis, a machine learning, based decision support model is developed to integrate resilience-related parameters with sustainability performance, with the aim of supporting ethically responsible and long-term sustainable global supply chains.

Table 4 *Comparison of Traditional vs. ML-Based Supplier Selection Approaches*

Criteria	Traditional Approach	ML-Based DSS Approach
Data Type	Limited to quantitative, structured data (e.g., cost, delivery time).	Integrates structured, semi-structured, and unstructured data (e.g., ESG reports, text).
Decision Criteria	Fixed, pre-defined, often subjective weights.	Dynamic, data-driven weighting using feature importance or ML optimization.
Adaptability to Change	Low - requires manual recalibration.	High - learns continuously from new data and evolving market conditions.
Transparency and Explainability	Moderate - dependent on analyst interpretation.	Enhanced with explainable AI models (e.g., SHAP, LIME).
Scalability	Limited for large datasets.	Highly scalable using big data and cloud computing frameworks.
Risk Detection	Reactive - identifies issues after they occur.	Proactive - predicts supplier failure or disruption risk before occurrence.
Sustainability Integration	Often qualitative and subjective.	Quantitative, using ESG indicators and predictive analytics.

Table 4 summarizes the conceptual flow of the proposed ML-based DSS for supplier selection. It begins with data collection from multiple sources, including financial records, supplier performance databases, sustainability reports, and external risk indicators. The preprocessing layer then cleans and normalizes these inputs before feeding them into different ML models for feature extraction, classification, and supplier scoring or ranking. The decision layer combines multi-criteria decision-making (MCDM) techniques with interpretability modules to generate final recommendations on the most resilient and sustainable suppliers. A feedback loop is also included, enabling the model to be continuously updated and improved as new data become available. continuously improved.

Research Problem

Small and medium-sized enterprises (SMEs) are particularly vulnerable to supply chain disruptions arising from natural disasters, financial instability, geopolitical tensions, and other unexpected events. Traditional supplier selection practices still focus primarily on economic criteria such as cost, quality, and delivery reliability. While these factors remain important, they largely overlook two critical dimensions: resilience and sustainability. Resilience reflects a supplier's ability to withstand and recover from disruptions, whereas sustainability relates to its environmental and social responsibility across the value chain.

In most existing approaches, resilience and sustainability are treated as separate or secondary considerations and are rarely integrated into a unified decision framework. This separation makes it difficult for decision-makers, especially in resource-constrained SMEs to systematically identify and priorities suppliers that perform well in both areas. As a result, firms remain exposed to avoidable risks, including operational disruptions, regulatory non-compliance, and reputational damage.

To address this gap, the present research proposes the development of a Resilient-Sustainable Supplier Selection System (RSSSS) as a machine learning based decision support system. The system is designed to predict and evaluate suppliers' resilience and sustainability performance simultaneously and to integrate these assessments into a structured selection process. By combining both dimensions within a single model, the proposed system aims to support more robust, data-driven supplier selection, reduce risk exposure, and enhance the long-term sustainability and resilience of SME supply chains.

Research Objectives

The main objectives of this research are:

1. To design and validate a comprehensive supplier evaluation model that integrates resilience and sustainability indicators, addressing gaps in traditional cost and quality focused selection methods and enabling holistic supplier assessment.
2. To develop a robust, machine learning driven supplier risk profiling framework that quantifies and evaluates suppliers' resilience and sustainability capabilities using historical, operational, and context specific data through predictive analytics.
3. To implement and evaluate machine learning algorithms for classifying and ranking suppliers based on resilience and sustainability metrics, thereby supporting data driven prioritization of suppliers.
4. To develop a lightweight, automated decision support system (DSS) tailored to SMEs that operationalizes the proposed models to detect, evaluate, and rank resilient-sustainable suppliers, reducing evaluation complexity and decision-making time.
5. To provide decision-makers with a transparent, interpretable, and data driven view of supplier strengths and weaknesses through an integrated visual dashboard, improving visibility of risk factors and sustainability indicators and enhancing trust in ML enabled decisions.

Research Hypothesis

This study hypothesizes that integrating sustainability criteria including economic, environmental, and operational dimensions with traditional resilience indicators, such as reliability, responsiveness, and agility, will enhance the accuracy of predicting supplier disruptions. By incorporating these sustainability factors, the research aims to develop a more comprehensive evaluation model that enables firms to select suppliers who are both adaptable to changing conditions and committed to sustainable practices.

The following hypotheses guide this research:

H1: Machine learning algorithms can accurately predict resilient-sustainable suppliers using historical data on resilience and sustainability, achieving statistically significant prediction performance.

H2: The Resilient-Sustainable Supplier Selection System (RSSSS) significantly outperforms traditional supplier selection models in terms of predictive accuracy, evaluation speed, and comprehensiveness in assessing resilience and sustainability.

H3: Integrating sustainability metrics (economic, environmental, and operational) into supplier evaluation significantly improves the overall resilience profile of the supply chain and reduces supply chain risk for SMEs.

In alignment with the objectives of this study, the formulated hypotheses provide a measurable framework for evaluating the effectiveness of the proposed Resilient-Sustainable Supplier Selection System (RSSSS) and its components.

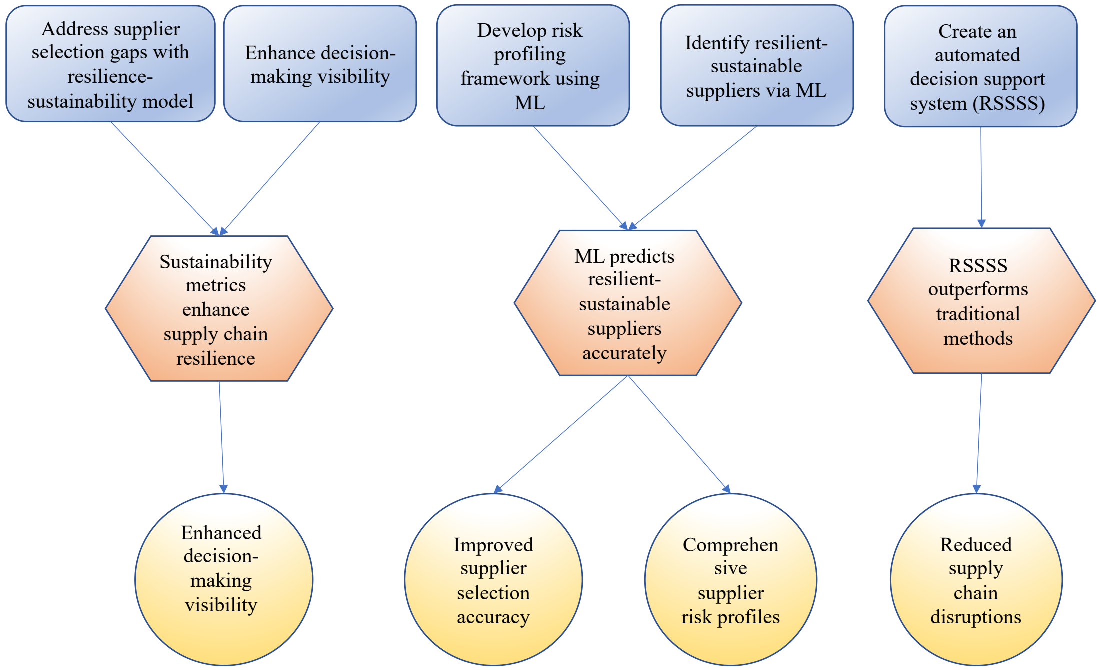
Hypothesis H1 posits that machine learning algorithms can accurately predict suppliers' resilience and sustainability based on historical data, directly supporting the objectives of developing a supplier risk profiling framework and identifying suppliers that meet resilient-sustainable criteria. This hypothesis addresses the technical feasibility of using data driven approaches to improve supplier selection beyond traditional cost focused methods.

Hypothesis H2 further strengthens the research framework by proposing that the RSSSS will outperform traditional supplier selection models in terms of predictive accuracy, evaluation speed, and comprehensiveness. This aligns with the objective of creating an automated, lightweight decision support system that overcomes the limitations of existing approaches and contributes to more robust, risk aware supply chain management.

Hypothesis H3, which suggests that integrating sustainability metrics enhances the overall resilience of the supply chain, underscores the need to expand traditional supplier evaluations to include environmental, economic, and operational dimensions. This hypothesis supports the objective of providing enhanced visibility for decision makers, enabling a comprehensive understanding of supplier strengths and risks.

Collectively, these hypotheses enable a rigorous examination of the validity of the proposed model and generate empirical insights that advance resilient and sustainable supplier selection practices in the supply chain literature.

Figure 6 *Flowchart of Research Objectives, Hypotheses, and Anticipated Outcomes for the Resilient-Sustainable Supplier Selection System (RSSSS) Study*



Research Aims

The overall goal of this study is to mitigate supply chain risks and enhance the sustainability and resiliency of the supply chain by providing a data driven, machine learning based approach to supplier selection and evaluation. In other words, the overarching goal of this research is to mitigate supply chain risks and enhance sustainability and resilience by developing a data driven, machine learning based approach to supplier selection and evaluation. This study specifically aims to investigate how the integration of sustainability metrics into the supplier evaluation model affects the resilience and risk profile of the supply chain, focusing on small and medium sized enterprises (SMEs). By examining the impact of combining sustainability and resilience measures on supplier selection and supply chain performance, this research seeks to address limitations in traditional supplier selection models and provide a more comprehensive decision-support tool for SMEs.

Contributions

This research introduced a comprehensive framework for the Resilience-Sustainable Supplier Selection System (RSSSS), which was designed to enhance decision-making processes in supply chain management. One of its primary contributions was the development of a centralized supplier database that gathered and stored all relevant data about analyzed suppliers. The database provided decision-makers with a unified platform to access supplier information, thereby facilitating both current evaluations and future improvements.

The system also aimed to reduce supplier-related disruptions by analyzing and understanding supplier behavior through advanced data-driven methods. By leveraging machine learning algorithms, the framework predicted the resiliency-sustainability level of each supplier and generated a corresponding risk profile, which enabled organizations to identify vulnerabilities within their supply chain. Additionally, the system calculated the probability of disruption occurrence for each supplier, thereby empowering decision-makers to proactively address potential risks.

A significant feature of the RSSSS was its ability to enhance visibility for decision-makers. By providing comprehensive insights into supplier performance, the system supported informed decision-making—allowing managers to determine whether to continue collaborating with a supplier, terminate the relationship, or invest in improvement. This structure ensured that manufacturers built stronger, more reliable supplier relationships, which ultimately enhanced overall supply chain stability.

Moreover, the system included automated reporting functionalities that provided manufacturers with detailed analyses of supplier performance, which were stored in the database for future reference. The scalability of the RSSSS ensured adaptability to the dynamic nature of supply chains, making it a robust solution that increased efficiency and resilience. Ultimately, this research contributed to sustainable supply chain practices by enhancing operational efficiency and supporting long-term sustainability objectives.

Conclusion

This research addresses a critical gap in supplier selection by integrating resilience and sustainability into a unified evaluation framework. Traditional supplier selection methods often prioritize cost, quality, and delivery time, while overlooking the interconnected importance of sustainability encompassing economic, environmental, and social dimensions, and resilience, understood as the ability to withstand and adapt to disruptions. These limitations expose businesses, particularly small and medium-sized enterprises (SMEs), to heightened supply chain risks and long-term inefficiencies.

To bridge this gap, the study proposes the development of the Resilient-Sustainable Supplier Selection System (RSSSS), which leverages machine learning algorithms to enhance predictive accuracy and streamline decision-making. By combining historical data on resilience and sustainability metrics, the system provides SMEs with a comprehensive, data-driven tool to identify and rank suppliers who not only meet performance requirements but also align with broader sustainability and risk mitigation objectives.

The research hypothesizes that this integrative approach will outperform traditional models by improving the accuracy of supplier disruption predictions, reducing supply chain risks, and enhancing decision-making efficiency. Through rigorous data analysis and model validation, the study aims to develop a robust, lightweight decision support system that enables SMEs to make informed, transparent, and effective supplier decisions.

Ultimately, this research seeks to contribute to the academic discourse on sustainable and resilient supply chain management while offering practical tools for SMEs. By emphasizing the strategic importance of incorporating both sustainability and resilience into supplier selection, the study advocates for a more holistic approach that benefits individual firms and supports broader environmental and social goals within global supply chains.

CHAPTER TWO

LITERATURE REVIEW

Introduction

Supplier selection is a foundational aspect of supply chain management (SCM), as it directly impacts operational performance, efficiency, and competitiveness in terms of cost. Traditionally, the main criteria for selecting suppliers have included cost, quality, and delivery reliability. These criteria have historically driven business decisions, as they are fundamental to optimizing operational workflows and ensuring profitability [39]. Cost management focuses on minimizing expenses, while cost leadership seeks to maintain competitive pricing for consumers. Likewise, high-quality standards are prioritized to ensure customer satisfaction and reduce defects. Delivery timeliness is also crucial to meet customer expectations and prevent delays in products or services [40]. However, while these criteria emphasize efficiency, they lack provisions for resilience, often leaving supply chains vulnerable to disruptions that impact stability.

As globalization expands, organizations have recognized the limitations of conventional supplier selection techniques. Modern supply chains are increasingly vulnerable to a variety of external challenges, such as natural disasters, economic shifts, political uncertainties, and operational failures [41]. For example, the COVID-19 pandemic highlighted the fragility of global supply chains, as businesses worldwide faced significant obstacles in accessing materials, maintaining production, and distributing products to customers [42]. This and other examples have underscored the necessity of resilience in supplier selection models, promoting criteria beyond efficiency to mitigate risks of supply disruptions effectively.

Supply risk resilience is defined as a supplier's capacity to maintain or quickly restore operations amid disruptions, a capability that includes reliability, flexibility, responsiveness, and risk management skills [43]. As global supply chains become more interconnected, resilience has become an essential criterion, especially for risk mitigation. However, resilience alone may not fulfill long-term sustainability goals. Increasing global attention to environmental and social issues has intensified the need for sustainable supplier practices, ensuring that supplier selection also aligns with sustainability goals [41]. Thus, focusing solely on resilience may overlook broader impacts and miss opportunities to advance both sustainable and robust supply networks.

Sustainability in supplier selection emphasizes environmentally friendly, compliant, and ethical practices. Managers today face considerable pressure from regulators, customers, and other stakeholders to achieve both cost-efficiency and environmental responsibility [44]. Sustainable procurement aligns with corporate social responsibility (CSR) principles, creating synergy between regulatory compliance and market perception. Firms that adopt sustainable supplier selection practices often experience enhanced reputation, regulatory adherence, and market advantage [45]. However, implementing sustainable criteria in supplier selection can present challenges, such as higher costs and resource demands, which may discourage smaller firms from integrating comprehensive sustainability metrics.

By addressing resilience and sustainability jointly, companies have the potential to construct supply chains that are both adaptable and durable. Yet, most traditional supplier selection frameworks fail to integrate these two interconnected elements, often treating them as isolated goals. For instance, a supplier's ability to mitigate ecological risks, such as adapting to climate change or complying with environmental laws, is a resilience factor that also contributes to sustainability [46]. Likewise, sustainable practices like waste reduction and energy efficiency foster resilience by lowering operational costs and reducing dependence on limited resources. This interconnectedness suggests that traditional models inadequately support the dual goal of resilience and sustainability, limiting their ability to foster a holistic approach to supplier selection.

Rapid technological advancements offer solutions to these challenges, particularly through data analytics and machine learning in supplier assessment. Machine learning facilitates the processing of vast datasets, enabling firms to predict supplier behavior, identify risks, and detect trends that could potentially disrupt operations. This data-driven approach equips organizations with actionable insights that support informed decision-making and risk management, fostering resilient and sustainable supply chains [47]. Therefore, while traditional supplier evaluation based on cost, quality, and delivery time remains relevant for managing resources, it lacks the capacity to fully address modern supply chain demands. Current challenges ,such as frequent supply disruptions and escalating consumer demands for sustainable practices, highlight the need for enhanced supplier assessment models. This literature review will explore resilience and sustainability within supply chain management (SCM), assess existing evaluation frameworks, and examine machine learning's role in refining supplier selection for long-term supply chain stability [24].

Supply Chain Management and Supplier Selection

SCM plays a pivotal role in today's business environment, as it coordinates the acquisition of materials, information, and finances essential for production and delivering finished products to customers. Within SCM, supplier selection is a key process that determines supply chain efficiency and performance. Traditionally, supplier selection focuses on three criteria: cost-efficiency, quality, and delivery reliability. These metrics are critical for optimizing administrative productivity and maintaining cost-effectiveness, especially for small and medium-sized enterprises (SMEs) with tighter profit margins [48]. However, these criteria focus primarily on immediate operational needs and may fall short of addressing broader, long-term challenges such as resilience and sustainability, which have become essential in managing modern supply chains [49].

In recent years, the limitations of conventional supplier selection criteria have become more evident, particularly due to the frequency of supply chain disruptions arising from global crises like the COVID-19 pandemic, geopolitical conflicts, and natural disasters. Such events highlight the necessity of incorporating resilience into supplier selection frameworks, defined as the ability of suppliers to withstand and recover from disruptions [50]. Resilience as a criterion is increasingly seen as a critical precursor to long-term stability in SCM. Simultaneously, sustainability in supplier selection is gaining significance, addressing the need for suppliers to uphold environmentally and socially responsible practices that align with evolving corporate governance standards

[51]. Organizations that ignore resilience and sustainability are at risk of operational disruptions and reputational damage, which can undermine their supply chain integrity and business reputation [52].

From an academic perspective, the literature reveals a scarcity of research that combines resilience and sustainability in supplier selection, a gap that is particularly critical for SMEs. Preliminary models in supplier selection focus on operational efficiency without accommodating the dynamic nature of today's supply chains [53]. This gap in adaptability is concerning, as SMEs often lack the resources to withstand supply chain disruptions. Moreover, evaluating suppliers' sustainability practices is challenging for many SMEs, as these suppliers might not possess well-established systems to monitor or report on their environmental or social impact [54]. The need to develop supplier selection frameworks that accommodate both resilience and sustainability is therefore clear, especially for SMEs that operate under resource constraints and are more vulnerable to external disruptions.

The distinct treatment of resilience and sustainability in supplier selection models is another challenge, despite their close interrelation. For instance, waste management and energy efficiency, which fall under sustainable practices, can simultaneously support resilience by reducing costs associated with scarce resources. Additionally, suppliers capable of adapting to regulatory changes and environmental risks are often more likely to engage in sustainable practices, suggesting an overlap that many selection models fail to address [55]. Authors, such as Guo et al. [55], argue for a more comprehensive approach to supplier selection that integrates both resilience and sustainability, which would better align supplier performance with modern SCM demands and strategic business goals. However, implementing such an integrated model remains challenging, particularly for SMEs, due to its complexity and the need for sophisticated data and analytical tools.

The advent of big data and analytics, especially through artificial intelligence (AI) and machine learning (ML), presents an opportunity to enhance supplier selection frameworks by integrating predictive analytics. By leveraging big data with machine learning, companies can forecast supplier performance on key metrics, including costs, quality, uptime, and sustainability, providing real-time insights into risk profiles and sustainability metrics [56]. Machine learning models, for example, can detect patterns in suppliers' historical performance, predicting potential disruptions and assisting companies in assessing supplier viability over time. These insights facilitate a data-driven approach to supplier selection that improves resilience and sustainability while aligning with SCM objectives [31].

However, despite these advancements, several barriers limit the application of these models, especially for SMEs. One major challenge is data availability, as machine learning models rely on historical data to make accurate predictions, and many SMEs lack the infrastructure or resources to gather and analyze such large datasets [57]. Additionally, the technical skills required to implement and maintain ML models can be prohibitive for smaller businesses, which may struggle to allocate the resources necessary for these sophisticated analytical tools. This technological gap suggests a need for more accessible solutions that enable SMEs to benefit from resilience and sustainability-focused supplier selection without extensive technical investment [58].

The literature from the past decade emphasizes the importance of integrating resilience and sustainability in supplier decision models to mitigate risks and enhance future performance. Yet, challenges remain, particularly for SMEs, due to the limited availability of data and the technical requirements of implementing advanced supplier evaluation systems. This gap presents a critical area for future research and development, aimed at providing accessible, effective tools to improve supplier selection frameworks.

Resilience in Supply Chains

In an increasingly unpredictable global environment, developing resilient supply chains has become essential for businesses. Supply chain resilience refers to the ability of a supply chain to anticipate, absorb, and recover from disruptions, whether due to natural disasters, political conflicts, financial crises, or operational issues within the organization. Globalization has further complicated resilience, as interconnected supply networks heighten vulnerability to external shocks, making resilience a critical driver of long-term sustainability [59]. Resilience has thus evolved from being merely reactive to encompassing proactive strategies aimed at preventing or minimizing the impact of disruptions. This shift in focus underscores the importance of evaluating suppliers based not only on traditional criteria but also on comprehensive risk profiles [60].

Key indicators of supply chain resilience include reliability, flexibility, responsiveness, and risk management capabilities. Reliability reflects a supplier’s ability to consistently meet delivery, quality, and timing expectations under both normal and disruptive conditions [61]. Flexibility refers to the capacity of a supplier to adapt production and delivery schedules when faced with unexpected changes. Responsiveness denotes a supplier's ability to engage in effective communication and cooperative problem-solving during emergencies. Finally, a proactive approach to risk identification and management is critical, allowing suppliers to anticipate and address potential disruptions. Fostering such resilience traits in suppliers aligns with the broader goals of SCM, emphasizing reliability and flexibility as vital elements in achieving resilience [62]. However, these factors present challenges for SMEs, which often lack the resources and technological capabilities to implement robust resilience strategies, leaving them vulnerable to disruptions in the supply chain.

Literature has revealed that SMEs face difficulties in embedding resilience into supplier selection processes. Financial and technological limitations hinder SMEs from conducting thorough risk assessments or employing advanced SCM tools, leading to reliance on conventional assessment methods. Many SMEs lack the infrastructure for real-time data analysis or predictive modeling, essential for accurately assessing risk profiles [63]. As a result, SMEs are often more susceptible to supply chain disruptions than larger firms, lacking both the flexibility to switch suppliers and the capacity to manage risk effectively. This disparity highlights an urgent need for resilience strategies that are accessible and scalable to SMEs, ensuring cohesive and stable supply chains across business sizes [64].

While traditional resilience models may appear unattainable for SMEs, recent studies suggest that alternative approaches can enhance supply chain resilience without requiring extensive resources. For instance, SMEs can diversify their supplier base and strengthen relationships with existing suppliers, adopting cooperative risk-sharing arrangements to mitigate individual vulnerabilities [65]. By collaborating more closely with suppliers and sharing risks, SMEs can build a more adaptable network that is better prepared to respond to disruptions. Furthermore, suppliers with an intimate understanding of potential risks are better positioned to identify and mitigate specific threats, a capability essential for effective resilience building [66]. These strategies suggest that, while sophisticated tools may be out of reach, SMEs can still enhance resilience by focusing on strong supplier relationships and diversifying sources.

Over the years, multiple frameworks and models have been proposed to measure and improve supply chain resilience. [62] introduced a resilience framework centered on stability margins and resilience capacity, highlighting the balance between supply chain risks and adaptive capabilities like flexibility, redundancy, and strong supplier relationships. This framework has since been adapted in various studies, proving applicable across different industries and supply chain structures. Expanding on this model, Aljohani [67] incorporated real-time data analytics, allowing companies to continuously evaluate supplier risk and resilience metrics as circumstances evolve. By adding predictive capabilities, this enhanced model supports a more dynamic approach to resilience, allowing firms to make real-time adjustments in supplier selection and management to adapt to changing risk landscapes. However, these advancements still face barriers in practical application, particularly for smaller firms with limited technological and financial resources.

The adoption of data analytics and machine learning in SCM offers promising potential for strengthening resilience, enabling organizations to leverage historical data to predict and manage supply chain disruptions. By applying machine learning, businesses can identify patterns in supplier performance and forecast potential disruptions, thus supporting more resilient supplier selection and risk management strategies [68]. For instance, predictive analytics tools can provide valuable insights into supplier credit risk, political risk, and environmental factors impacting supply chain stability, allowing companies to choose suppliers capable of withstanding potential threats [55]. These capabilities are especially valuable in configuring supply chains that are both resilient and sustainable, helping businesses select suppliers who can endure and quickly recover from disruptions.

Nevertheless, many SMEs encounter barriers to adopting such advanced technologies, primarily due to limited financial resources and insufficient technical expertise. Studies show that, while larger firms are increasingly integrating machine learning into SCM, SMEs often rely on traditional tools, facing limitations in data analysis and risk assessment [69]. This gap underscores the need for simplified and accessible tools that SMEs can use to enhance resilience without requiring extensive technological investment. For SMEs to adopt a resilience framework, lightweight, cost-effective solutions that are easy to implement and maintain are essential.

In conclusion, resilience is a strategic imperative in SCM, essential for helping businesses withstand disruptions and ensure continuity. While larger companies are leveraging advanced data analytics and machine learning to enhance their supply chain resilience, SMEs can also build more resilient supply chains by diversifying suppliers, sharing risks, and strengthening communication within their networks. As supply chains grow in complexity, incorporating resilience factors into supplier selection processes will be critical for achieving long-term stability and success.

Sustainability in Supply Chains

Sustainability in supply chain management (SCM) has gained significant attention due to increased pressure from consumers, governments, and investors for organizations to adopt greener practices. Unlike cost-cutting or efficiency-focused strategies, sustainable SCM incorporates long-term goals aimed at stabilizing economic futures, minimizing environmental harm, and delivering social benefits. This approach aligns with the "triple bottom line," which emphasizes economic efficiency along with environmental and social impacts [70]. Sustainability’s relevance in SCM becomes particularly evident in large, complex supply chains, where monitoring all suppliers closely poses a challenge. Sustainable development goals require businesses to implement practices that reduce waste and carbon emissions while supporting ethical standards across the supply lifecycle, from procurement to distribution.

Stakeholder expectations are among the main drivers prompting companies to adopt sustainability in their supply chains. Many nations have established stringent environmental laws mandating organizations to reduce greenhouse gas emissions, minimize waste, and uphold fair labor standards [71]. Consumers are also increasingly drawn to brands that demonstrate environmental responsibility, with studies indicating consumers’ growing willingness to pay premium prices for products that prioritize sustainability [72]. Therefore, suppliers integrating sustainability within their operations fulfills legal and ethical obligations while also gaining competitive advantages, including enhanced brand image and consumer preference.

While sustainability demands can increase operational costs, sustainable practices can also improve efficiency by reducing waste and energy expenses. Hossain et al. [73] corroborated this view, noting that companies integrating Lean Six Sigma methodologies with sustainability goals report significant cost savings due to reduced material and energy use. These practices not only lower expenses but also bolster the flexibility and robustness of supply chains. Suppliers relying on renewable energy, for example, are less affected by fluctuations in fossil fuel availability or pricing, thus enhancing the resilience of supply chains. Similarly, Hamid [74] emphasized that sustainable construction and energy management practices help reduce climate impact, ensuring long-term adaptability and economic performance. However, critics argue that although these practices bring long-term gains, they impose immediate costs, which can be burdensome for SMEs, often constrained by limited financial resources.

The connection between sustainability and resilience has gained recognition in recent years. Analyses suggest that sustainable supply chains are better positioned to withstand disruptions due to their focus on stability and risk mitigation [75]. For instance, companies sourcing materials from suppliers who prioritize environmental and social responsibility are less likely to face disruptions from resource shortages or shifting regulations, as these suppliers are typically more adaptive to such challenges [76]. Additionally, sustainable companies often form stronger partnerships with their suppliers, working collectively towards shared sustainability goals. These collaborative relationships foster mutual trust and enable better coordination during disruptions, enhancing the responsiveness and adaptability of the supply chain [77]. Yet, skeptics argue that focusing too heavily on sustainability might slow market responsiveness and increase complexity, which could be counterproductive for organizations prioritizing agility.

However, despite its advantages, implementing sustainability in SCM poses challenges, especially for SMEs. High costs associated with sustainable practices discourage SMEs, which often operate on limited budgets. Many lack the human resources or technical expertise required to systematically monitor and assess supplier sustainability performance [78]. To address these barriers, recent studies have advocated for practical tools and frameworks tailored to enhance sustainability in SMEs' supply chains. These frameworks provide guidelines for sustainable supplier selection, allowing SMEs to balance cost, quality, and sustainability factors in their decisions. Such tools could empower smaller firms to implement sustainability practices effectively, albeit on a scale that fits their resources and capabilities [79].

In conclusion, sustainability has evolved from an optional addition to an essential component of long-term SCM success. Beyond regulatory compliance and public perception, integrating sustainability offers operational benefits, such as cost efficiency and supply chain reliability. However, SMEs and socio-economically focused organizations face unique challenges in adopting these practices, often due to financial limitations and complexities. Addressing these issues calls for accessible, scalable tools that support SMEs in aligning with sustainability goals, paving the way for future research to develop solutions that bridge this implementation gap.

The Triple Bottom Line (TBL) in Sustainable Supply Chains

The ideas of the Triple Bottom Line (TBL) were drivers of the discussion on sustainability, as it should be emphasized that the performance of business can be determined not only by financial profit (Profit) but by social (People) and environmental (Planet) performance as well[55]TBL, initially popularized by John Elkington in the middle of the 1990s, asks organizations to consider broadening their bottom line orientation beyond a single emphasis on economic indicators to include a threefold stream of domains of value (Investopedia). Supply-chain The TBL framework has taken root, though, due to the supply networks of modern times, which all interact around the environmental, social, and economic systems; changes or irresponsible practices in one of the systems tend to spread to the others. Indicatively, suppliers, which undermine environmental laws, can also create reputational, regulatory, or operational risk, impacting the cost and profitability.

TBL framework can be used as a framework in the area of sustainable supply chain management in an aspect of review of supplier selection, partnerships, and supply-network design. Recent empirical studies point out that the three dimensions, that is, economic, environmental, and social are not isolated factors, these dimensions interact and affect each other mutually when it comes to the resilience and sustainability of the supply chain. Considering a research conducted by [80] based on structural-equation modelling indicates that personal sustainability variables aligned with TBL have a significant impact on supply-chain resilience (Frontiers). The reason is that the authors identify a knowledge gap: despite numerous studies enumerating sustainability variables, some are not anecdotal in determining which of the TBL variables most affect resilience and how. This gap is applicable when developing decision-support systems to evaluate suppliers since this gap implies that dimensions of TBL should be operationalized and not considered as abstract concepts of sustainability.

Regarding the economic aspect, TBL integrates organizations and their supply-chain partners to take into account not only the cost, profit, and efficiency, but also the long-term value creation, resource efficiency and risk mitigation. On the environmental element, the aspect of attention becomes resource consumption, pollution, waste, emissions, closed loop systems and eco-designs in the supply chain. At the societal level, labor practices, impact on communities, health and safety, human rights and fair relationship with suppliers are analyzed by firms. The 2025 review by [81] states that the economic bottom line is less cumbersome to measure whereas the social and environmental elements need to be integrated with more sophisticated metrics and frameworks. Practically, it implies that supply-chain decision-makers, notably those involved in supplier selection have to make trade-offs involving the 3Ps (Profit, People, Planet) as opposed to falling back to affordability standards.

A risk-conscious supply-chain strategy can be achieved especially when TBL is integrated with resilience. Suppliers with good performance at either an environmental or social level tend to be better governed and with stronger management systems along with high levels of transparency-values that are also associated with quicker recovery, adaptability, and disruption alleviation. That is, implementing TBL in supplier assessment can be used to increase supply-chain resiliency, not only sustainability per se. Tundys and Wiśniewski [80] have discovered that particular TBL-specific variables (which include environmental management systems and social engagement) not only have a positive correlation with resilience capabilities within supply chains but also statistically contribute to the outcome. Nevertheless, numerous supply-chain models continue to focus on cost, quality, and lead-time performance, and have the TBL dimensions on the nice-to-have-list instead of to the category of critical decision factors.

Relating to supplier choice as applied to the SMEs or network partners, the TBL platform presents the opportunities and challenges. On the one hand, TBL alignment can be used by SMEs as a competitive advantage, create reputational capital, obtain long-term contracts, and correspond in the demands of large buyers to sustainability. Conversely, SMEs have relatively limited resources, and it is hard to plan and control TBL performance because of limited budget, technological maturity, and managerial bandwidth. Empirical research by [82] points out that sustainable supplier selection research has been done, but not that many frameworks have combined TBL metrics in a manner that would be practical among SMEs in developing economies. This leaves a literature gap: How should decision-support systems (DSS) or machine-learning-based structures operationalize TBL criteria, with respect to supplier selection in an SME It is the solution to this gap which is central to the dissertation focus namely the resilient-sustainable supplier selection system (RSSS) of multi-SDN controllers- by analogy, the

SMEs (with small capacity yet high-relevance in the resilience networks) can be handled in this way.

The last one is related to measurement and operationalization. Although the concept of TBL framework is generally accepted through research, the practical implementation of the framework in the evaluation of suppliers is usually disjointed. Recent studies in the textile sector [83] suggest a model that combines TBL with SWARA and TOPSIS technique to assess the suppliers in the Bangladesh SME setting. This shows how there is a transition to multi-criteria decision-making (MCDM) tools that incorporate TBL metrics. However, the difficulty is in adding dynamic and real time information and decision-making potential (such as through DSS or machine-learning) to turn TBL into action, and not symbolic.

The Intersection of Resilience and Sustainability

The intersection of resilience and sustainability in supply chains represents a paradigm shift where both constructs are not only considered but integrated to drive long-term supply chain robustness and environmental responsibility. Traditionally, resilience refers to a supply chain's ability to withstand disruptions, while sustainability emphasizes environmentally and socially responsible practices. Recent studies argue that these two factors, previously treated as distinct, are essential to formulating a future-ready supply chain [39]. By approaching resilience and sustainability as complementary rather than independent constructs, organizations can address supply chain vulnerabilities while simultaneously adhering to environmental and social governance standards.

Studies by Wu et al. [39] and Ivanov and Dolgui [66] underline the practical benefits for SMEs of selecting suppliers who prioritize both sustainable practices and resilience. Suppliers who implement environmentally friendly practices, such as waste reduction and renewable energy, not only fulfill sustainability goals but also tend to have strong risk management protocols, enhancing supply chain resilience. This dual capacity is particularly beneficial for SMEs that lack the resources to switch between suppliers in the event of disruptions, making resilient and sustainable supplier partnerships critical.

Furthermore, emerging technologies such as machine learning and fuzzy logic-based decision models have enhanced supplier selection processes, enabling real-time assessment of supplier resilience and sustainability indices. Studies using the Best Worst Method (BWM) and fuzzy modeling approaches, as applied by Bonab et al. [41], demonstrate how these models can prioritize suppliers based on adaptability, risk management, and sustainable practices, creating a balanced and adaptable supplier selection framework.

Despite the advantages, implementing this integrative model in SMEs remains a challenge. Limited capital and lack of technological infrastructure inhibit SMEs from fully benefiting from advanced data-driven supplier evaluations [84]. Yet, studies suggest feasible strategies, such as diversifying suppliers and fostering partnerships, to mitigate these challenges without heavy financial investment [39]. These approaches allow SMEs to develop resilience and sustainability capabilities without depending solely on costly technological solutions, positioning them better to meet evolving regulatory and market demands.

Ultimately, aligning resilience and sustainability in supplier selection not only enhances supply chain adaptability but also strengthens a company's market position as environmentally and socially responsible. Continued research emphasizes that such integrative models are not only strategic but increasingly imperative as supply chain networks expand globally and face heightened vulnerability to disruptions.

Machine Learning in Supplier Evaluation

The integration of machine learning (ML) in supplier evaluation within SCM is transforming traditional supplier assessment practices by allowing companies to predict supplier resilience and sustainability. By analyzing supplier performance, ML models, particularly through algorithms like Random Forest and Support Vector Machines (SVM), offer predictive analytics that assess suppliers' reliability and anticipate potential risks [56]. Thomas and Sandeep [85] investigated ML's role in refining big data evaluation models, emphasizing how these techniques enhance supplier reliability predictions. Similarly, Thakur et al. [86] illustrated that ML algorithms improve disruption forecasting, which significantly strengthens suppliers' resilience.

One of the primary advantages of using ML in supplier evaluation is automation, which allows for efficient, real-time decision-making. Automated ML processes in SCM supply critical insights on supplier reliability and sustainability, thereby reducing the time and labor typically required for traditional assessments. These advancements are essential for real-time supply chain operation, where immediate risk control and predictive capabilities are necessary [87]. Nevertheless, SMEs face notable barriers when integrating ML solutions, such as high risks, limited data, and a lack of skilled personnel.

While these constraints may hinder ML implementation efficiency, the potential benefits for SMEs, such as increased resilience and streamlined evaluation, are promising [66].

In recent years, decision support systems (DSS) have increasingly incorporated machine learning and multiple criteria decision-making (MCDM) methodologies to handle the complexity of supplier evaluations. Ma and Li [88] introduced an innovative DSS model that modifies traditional MCDM approaches using ML to address supplier evaluations with both quantitative and qualitative data. This framework enables organizations to efficiently analyze a broad array of suppliers and products, enhancing SCM decision-making capabilities. By leveraging ML in DSS, companies can achieve improved supplier selection processes that account for resilience, sustainability, and operational efficiency, paving the way for more robust and responsive supply chains.

The Role of Small and Medium Enterprises (SMEs)

Definition and Global Significance

Small and Medium-Sized Enterprises (SMEs) represent the heart of the economic systems of the nation and the world in general. The World Bank (2024) states that SMEs cure no less than 90% in the admission of business as well as reserved more than half the world labor, at a time dearer to half the GDP in developing economies[89] .They are agile and deeply embedded in local supply networks, which allows them to contribute to innovation and development of the region, employment, and communities. SMEs play vital into-and-out-of-global-corporation critical intermediary functions, as a component manufacturer, logistic service provider, or niche service provider; in a supply-chain environment, linking local ecosystems with global corporations [90]. Due to this embeddedness, resilience in SME has a direct connection to overall outcomes of supply-chain continuity and sustainability.

SMEs have a high vulnerability to external shocks like pandemics, shortages of raw materials, and geopolitical disruptions in spite of their strategic role because they are usually constrained by their financial, human, and technological resources. According to [91], the COVID-19 crisis has demonstrated structural weaknesses in the supply chain of SMEs as they were over-dependent on a limited number of suppliers and lacked digital monitoring systems. This weakness underscores the necessity to incorporate digital decision support systems and sustainability indicators in processes of SMEs in an effort to enhance adaptability.

Major SMEs Issues in Supply Chain Sustainability.

SMEs are faced with numerous obstacles in their pursuit of meeting the goals of sustainability and resilience. The key threats are that lack of financial resources, insufficient digital maturity, and a lack of standardized data on ESG [92]. Economically, SMEs do not have the cash flow to invest in sustainability certification, energy-saving technologies, or redundancy planning and therefore decision making is short term as to ensure the survival rather than the risk handling in the long term. On the digital front, SMEs do not use enterprise-resource-planning (ERP) and analytics systems as rapidly as large businesses do, thus limiting their capacity to gather and review supplier-performance information.

Systemic challenges continue to shape the capacity SMEs to achieve both resilience and sustainability within their supply chains. These challenges span financial, technological, human, regulatory, and operational domains, each imposing distinct constraints on organizational adaptability. Financial limitations, such as restricted access to credit and the high costs associated with compliance and technology adoption, hinder SMEs from investing in sustainable technologies and implementing robust risk-mitigation strategies [93]. Similarly, technological immaturity manifested through limited data collection, poor analytics capacity, and insufficient digital infrastructure reduces supply chain visibility and predictive capability. Human capital shortages further exacerbate these challenges, as the lack of skilled professionals impedes the effective deployment of decision-support systems and the integration of sustainability and analytical practices into daily operations [94].

Beyond internal factors, external pressures from complex regulatory and ESG frameworks create additional barriers. Inconsistent disclosure requirements and the absence of standardized reporting formats increase compliance burdens and limit SMEs' ability to compete in sustainability-driven markets. Operational vulnerabilities, including dependence on limited suppliers and weak logistics redundancy, heighten exposure to disruptions and market shocks, ultimately threatening continuity and competitiveness [95]. Collectively, these systemic rather than firm-specific constraints underline the fragility of SMEs in sustainable supply chains. Overcoming them requires the development of lightweight, cost-efficient digital solutions capable of automating data management, supporting decision-making, and facilitating sustainability reporting without overextending limited organizational resources. Such innovations offer a strategic pathway for enhancing SME resilience and advancing the broader agenda of sustainable supply chain transformation.

Supplier Relationships and SMEs

The competitiveness of the SMEs depends on the supplier relationships. SMEs tend to be in the tier-2 or tier-3 category of supply networks where they depend on their suppliers as well as their purchasers. The instability of one of the links, therefore, is likely to impact SME activities out of proportion. Authors [96] state that diversified supplier base and collaborative relationships led to quicker recovery in SMEs associated with global disruptions as compared to firms involved in cost-oriented sourcing approaches.

SMEs can have a greater buffering effect against shocks in case of long-term relationships founded on transparency, joint sustainability targets, and risk-sharing systems. In addition, the existence of sustainable supplier relationships may help SMEs to expand their accessibility to the international markets, since large purchasers tend to be stricter in their procurement policies, introducing requirements to use the suppliers that are sustainable. Thus, monitoring and provision of meeting the environmental and social standards will become a condition of market entry by SMEs.

Integrating Triple Bottom Line (TBL) Principles in SME Operations

Implementing the Triple Bottom Line (TBL) framework such as economic performance, environmental performance and social performance is especially a difficult undertaking in the case of SMEs because of cost and data limitation. However, various research indicates that SMEs that have sought easier or gradual sustainability practices have quantifiable advantages in efficacy and reputation. In a study in Brazilian manufacturing SMEs, determined that low-cost environmental management systems and stakeholder trust programs enhanced because they integrated low-cost and community engagement systems [97].

Adoption of TBL in SMEs therefore has two roles in increasing resilience through less dependence on limited resources and increasing sustainability through aligning the operations with the regulation and societal expectations. But TBL metrics need to be scaled to the realities of SMEs, i.e. with qualitative over quantitative measurements and with key performance indicators (KPIs) that are easy to compute and to access as opposed to sophisticated quantitative audits that are appropriate to large companies [98].

Decision support systems (DSS) and digital enablement of SMEs.

Digital Decision Support Systems (DSS) present a valuable opportunity for small and medium-sized enterprises (SMEs) to operationalize sustainability and resilience frameworks within their operations. Contemporary DSS integrate analytical dashboards, predictive algorithms, and scenario simulations to support managers in identifying supplier-related risks and evaluating trade-offs between cost, resilience, and sustainability.

Cloud-based DSS solutions are particularly advantageous for SMEs, as they require minimal investment in IT infrastructure and offer scalable functionality according to organizational needs. As [99] highlights, the implementation of machine learning (ML)-based DSS significantly enhances the speed and reliability of decision-making in SMEs, especially under conditions of uncertainty. These tools enable small businesses to harness the power of predictive analytics without the need to employ dedicated data science teams.

However, the key to unlocking the full potential of these systems lies in the SMEs' ability to tailor DSS interfaces, cost structures, and data requirements to align with their specific capabilities and resource constraints.

Gaps in the Literature

While resilience and sustainability have received considerable attention in the context of supplier selection, there is limited research that offers fully integrated models combining both dimensions within a machine learning, based framework. Existing approaches typically address either resilience or sustainability in isolation, or treat them as separate components, leading to fragmented and incomplete supplier evaluation processes [100].

Although machine learning (ML) has shown strong potential for advancing supplier evaluation, its use for jointly modelling resilience and sustainability remains underdeveloped—particularly in the context of SMEs, which often face constraints related to data availability, technical expertise, and financial resources [101].

These limitations highlight the need for a unified model, such as the proposed Resilient-Sustainable Supplier Selection System (RSSSS), that leverages ML to provide a comprehensive assessment of suppliers' resilience and sustainability, thereby supporting more informed and robust supplier selection decisions.

Table 5 *Summary of Related Work*

Reference	Method / Approach	Dataset / Context	Main Findings / Contribution	Identified Gaps / Limitations
[102]	MCDM aggregation + machine learning	Automotive industry data	Proposed a model that combines multi-criteria decision-making (MCDM) with ML to enhance the reliability of supplier evaluation and selection.	Does not explicitly address SME constraints or real-time decision-making support.
[103]	AI-based multi-criteria decision making	Literature review	Derived policies and criteria related to sustainability and resilience for supplier selection using AI-based MCDM concepts.	Primarily conceptual; limited attention to realistic implementation of AI-based solutions in SMEs.
[56]	Random Forest, SVM	Simulated supply chain data	Applied ML methods to analyze and predict supplier-related factors and risks, improving risk and sustainability assessment in a simulated supply chain context.	Relies on simulated data; SME-specific, real-world datasets are not adequately incorporated.
[104]	Resilient supply chain model + AI	Various industries (secondary data)	Outlined how AI can strengthen supply chains in the post-COVID-19 context, with emphasis on resilience at the network level.	Does not specifically target supplier selection or jointly integrate resilience and sustainability in a concrete evaluation model.
[105]	Fuzzy MCDM	Multi-sector data (social and environmental indicators)	Proposed a fuzzy MCDM framework that merges sustainability and resilience criteria for supplier selection under uncertainty.	Lacks dynamic, data-driven decision-making using advanced ML; focuses on fuzzy logic rather than learning from large-scale historical data.
[31]	Hybrid ML + simulation (digital twins)	Construction sector data	Employed digital twins and ML to simulate supplier selection scenarios and support resilience-building in construction supply chains.	Relies on data-intensive modelling that may be difficult for SMEs to implement; limited consideration of SME data and resource constraints.

Table 5 cont'd

Reference	Method / Approach	Dataset / Context	Main Findings / Contribution	Identified Gaps / Limitations
[106]	Deep learning (LSTM)	E-commerce supplier reviews	Used deep learning to estimate supplier performance from customer review text, contributing to sustainable supply chain management by leveraging qualitative feedback.	Uses only qualitative review data; does not include quantitative performance indicators or explicit resilience/sustainability metrics.
[107]	Supervised ML, data-driven simulation	Manufacturing data (digital manufacturing context)	Introduced a simulation-based, supervised ML approach for selecting resilient suppliers in digital manufacturing, focusing on disruption risk.	Focuses primarily on resilience; does not integrate sustainability as a core evaluation dimension.
[20]	Multi-agent system + Big Data analytics	Construction industry data	Proposed a multi-agent system supported by big data analytics to improve supplier selection and coordination in construction supply chains.	Limited discussion of practical constraints faced by SMEs, such as limited IT infrastructure and implementation capacity.
[108]	Multilayer Perceptron (MLP) classifier	Dataset of 100 suppliers	Developed ML-based classification models to group suppliers into efficient and inefficient classes; the MLP model achieved the best performance and was shown to be applicable to real supplier selection problems.	Focuses mainly on efficiency-based classification; does not explicitly integrate resilience and sustainability as multi-dimensional constructs; small sample size and no explicit SME focus.
[109]	Hybrid machine learning + risk profiling (RSSS)	Historical supply chain data from SME-based manufacturing simulations	Proposed a two-layer Resilient Supplier Selection System (RSSS) integrating ML with supplier risk profiling; achieved accurate classification of resilient vs. non-resilient suppliers and enabled adaptive decision-making using behavioral risk indicators.	No real-world implementation reported; does not incorporate sustainability (environmental/social) criteria; focus is limited to resilience and risk without a full resilience-sustainability perspective.

As Table 5 illustrates, there are notable gaps in current models for supplier selection that address resilience and sustainability, particularly in integrating both dimensions cohesively. Existing methodologies like MCDM, fuzzy models, and even machine learning approaches often lack real-time adaptability, especially when applied within the constraints of SMEs. For example, while [102] employed MCDM-aggregation with machine learning, the application is limited in terms of real-time response—an essential factor in dynamic supply chains. Additionally, papers by [107] and [20] proposed models that either focused on one dimension (e.g., resilience without sustainability) or presented advanced frameworks that may be too complex or resource-intensive for smaller enterprises.

To bridge these gaps, the present research proposes the Resilient-Sustainable Supplier Selection System (RSSSS), which integrates resilience and sustainability criteria through a machine learning-based solution. RSSSS not only enables simultaneous evaluation of both resilience and sustainability factors but also offers an adaptable, real-time assessment framework designed to meet the needs of diverse business environments, including those of SMEs. This approach leverages predictive analytics to optimize supplier selection, ensuring that resilience and sustainability are core considerations in the decision-making process.

Conclusion

Reviewing the literature underscored the growing need for integrated supplier selection models that incorporate resilience and sustainability, recognizing these factors as interlinked components essential for long-term supplier relationship management. Emerging technologies, like predictive analytics and machine learning offer significant potential in this area, providing real-time insights that can enhance both supplier resilience and sustainable practices. However, current models, especially those accessible to SMEs, often lack the robust framework necessary to support effective resilience-sustainability integration.

The proposed Resilient-Sustainable Supplier Selection System (RSSSS) is designed to bridge these gaps, providing a comprehensive, data-driven solution tailored for resilient and sustainable supplier evaluation. By leveraging insights from this review, RSSSS aims to address the limitations highlighted in existing literature, offering a methodology that supports SMEs and other organizations in selecting suppliers who contribute to both resilient and sustainable supply chains.

CHAPTER THREE

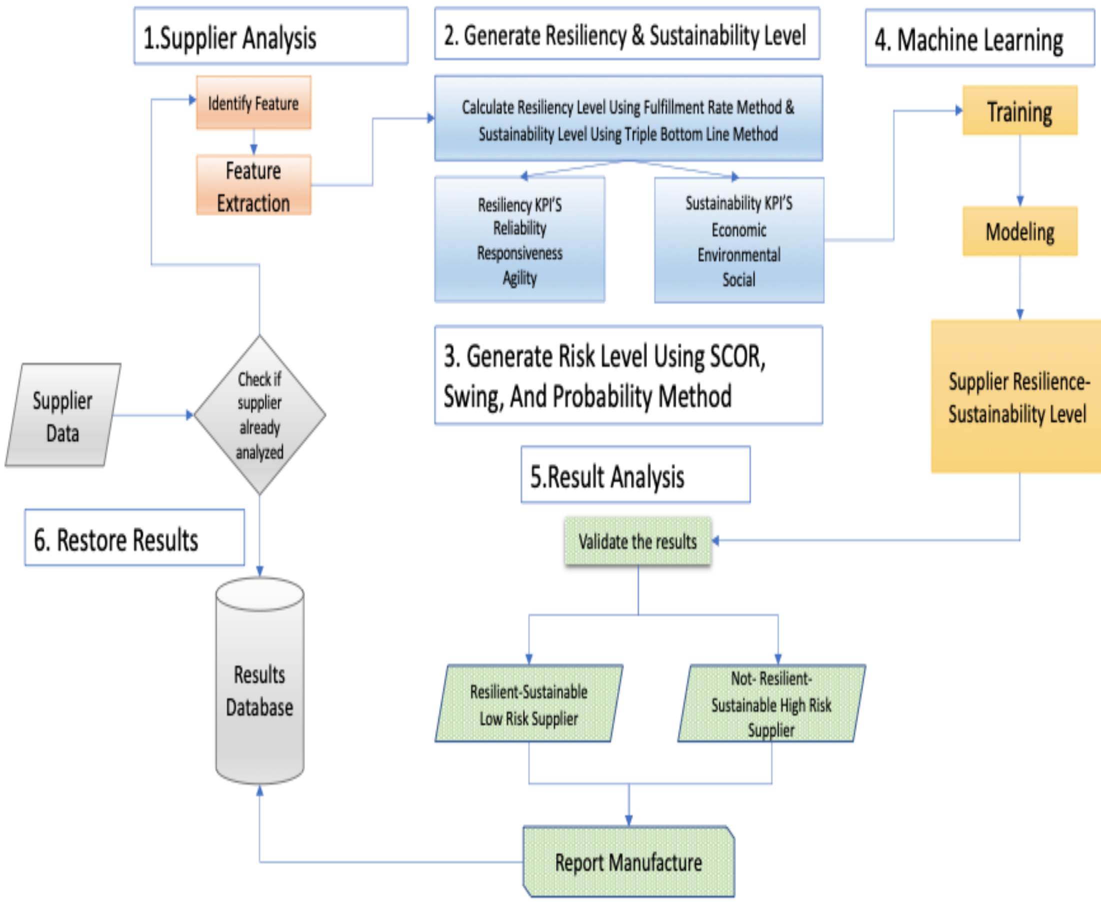
METHODS

Methodology

The system operated through a six-step process designed to predict the resilience and sustainability levels of any supplier entering the system and to determine the associated risk level. When supplier data were entered into the system, it checked whether the data had already been analyzed. In the event that the data had already been analyzed, the system proceeded from the first step (supplier analysis) to the second step (generation of resiliency and sustainability levels). If not, static analysis techniques were applied to extract relevant features from the supplier's historical data. A resilience and sustainability level were then generated, primarily based on the supplier's fulfillment rate and the Triple Bottom Line method. Afterwards, the risk level was determined using managerial and quantitative methods, including the Supply Chain Operations Reference (SCOR) model, Key Performance Indicators (KPI), Swing Weighting, and probabilistic risk assessment.

By closely linking resilience and sustainability, the system provided a holistic assessment of each supplier's overall performance, helping decision-makers understand the strengths and weaknesses of their suppliers in order to support informed decision-making. The design of the RSSSS system model and its implementation were elaborated upon in Figure 2.

Figure 7 *System Model*



The RSSSS consisted of two primary processes: static and dynamic, as shown in Figure 7 In the static phase, the RSSSS calculated the Supply Chain Operations Reference (SCOR) model, along with its Key Performance Indicators (KPIs), the swing weighting method, and a probabilistic risk assessment to calculate the supplier's risk level. Following the static process, the dynamic process began by applying supervised machine learning algorithms that integrated the supplier's risk level generated in the static phase to refine the supplier's resiliency-sustainability level. The system proceeded to validate the results, report them to the manufacturer, and store the outcomes in a database for future reference. The entire system operated through six main stages, as follows:

Supplier Analysis Stage: In this stage, supplier data were examined and analyzed using static analysis techniques, based on historical data, to identify relevant features. Key features, such as delivery lead time, capability, distance or location, delivery method, incoming quantity, PO quantity, and agility, were extracted. This stage, also referred to as the pre-processing stage, helped in identifying the features that might influence the final results and ensured that only the most relevant data were used for further analysis. Moreover, each of the extracted features underwent a pre-processing phase to transform the data into a suitable format for machine learning algorithms. This process involved several steps, including data cleaning, normalization, encoding of categorical variables, handling of missing values, and feature scaling.

Generate Resiliency-Sustainability Level Stage: In the static stage, a resiliency-sustainability level was generated for the analyzed supplier based on two key factors: the fulfillment rate and the Triple Bottom Line (TBL) method.

Equation 1 demonstrates how the resiliency level was calculated based on the supplier’s fulfillment rate.

$$\text{Resiliency Level} = (\text{Fulfilled Orders} / \text{Total Orders}) \times 100$$

Equation 2 shows how the sustainability level is calculated using the Triple Bottom Line method, which incorporates the supplier's performance across three dimensions—economic, environmental, and social:

Sustainability level = (Economic Performance + Environmental Performance + Social Performance) / 3

The literature has presented diverse approaches to weighting each dimension, ranging from equal distribution to context-specific prioritization based on industry requirements, stakeholder influences, or empirical evidence. In a study by Tarne et al. [110], decision-makers assigned nearly equal importance to economic (33.5%), environmental (35.2%), and social (31.2%) dimensions, supporting the validity of an equal weighting approach. This aligns with the current study's methodology, ensuring a balanced assessment of sustainability in line with the Triple Bottom Line framework.

1. **Generate Risk Level Stage:** In this stage, we integrated both static and dynamic processes to assess the risk of suppliers SCOR, Swing, and Probability methods. The swing weighting method was applied to assess factors, like delivery lead time, supplier capability, and agility. These methods were combined to calculate the probability of disruption for each supplier. This probability was dynamically refined through supervised machine learning algorithms. These resiliency-sustainability KPIs were combined with the probability of disruption to generate the final risk level. The risk level was calculated by multiplying the probability of disruption by the impact, where the impact was represented by the supplier's resiliency-sustainability level, including economic, environmental, and social aspects. This calculation was expressed in Equation 4.3 of the probabilistic risk assessment:

   Equation 3 $R=P\times I$

Where:

- R is the risk level,
- P is the probability of disruption, and
- I is the impact, which accounts for the supplier's resiliency and sustainability across economic, environmental, and social dimensions.

2. **Machine Learning Stage:** In this stage, the supplier's static data were used to train the machine learning model, which was then applied using appropriate regression algorithms. The system evaluated different models during the testing phase to determine the best-fitting function. Once the optimal model was selected, it was used to generate the resiliency-sustainable level for each supplier.
3. **Results Analysis Stage:** In this stage, the system validates the results to determine whether a supplier was resilient-sustainable, indicated by a low risk in their supply processes, or not resilient-sustainable, which was reflected by a high risk in their supply processes. The validation process was performed using performance metrics, such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the R^2 score. As the final phase of this stage, the system generated a report for the manufacturer, detailing the supplier's resiliency-sustainability level and providing a comprehensive explanation of the supplier's weaknesses. This report helps decision-makers better understand the risks associated with each supplier and take appropriate actions accordingly.

4. **Restore Results Stage:** In this stage, reports for all analyzed suppliers were stored in the results database. When a new supplier was introduced, the RSSSS will first check the database to see if an existing analysis for that supplier was already available.

Implementation

In this section, the design and implementation of RSSSS were discussed in more detail by elaborating the technical details of each stage. As discussed previously, RSSSS 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) Data Entry and Condition Check:

Suppliers' data were entered into the system, and a condition check was applied to determine if the supplier has already been analyzed.

- If the supplier had been previously analyzed, the supplier entry is retrieved from the database.
- If the supplier had not been analyzed, the system proceeded to the supplier analysis stage for further processing.

The data were received through multiple channels, including direct integration with enterprise systems, such as ERP or procurement software, manual data uploads by manufacturers, or automated data collection from suppliers via secure API connections. This process ensured flexibility and compatibility with various data sources while maintaining data integrity and security.

(b) Static Analysis and Feature Extraction:

In the first step of static analysis, supplier data from historical records were examined and analyzed to identify available features. Functional features of suppliers were extracted, including:

- Delivery Lead-Time: Analyzing incoming quantity and purchase order (PO) quantity to assess delivery reliability.
- Capability: Evaluating the supplier's ability to meet required operational demands.
- Distance or Location: Considering the supplier's geographical proximity to the manufacturing facility.
- Delivery Method: Assessing the supplier's transportation and delivery mechanisms.
- Agility: Measuring the supplier's responsiveness to sudden changes or disruptions.
- Sustainability Practices: Extracting data on carbon emissions, waste management, and compliance with environmental standards.

The extraction was performed by integrating supplier data from multiple sources, such as ERP systems, procurement software, and supplier portals. Data cleaning ensured accuracy and consistency, while feature engineering techniques were applied to derive meaningful insights. Advanced methods, such as rule-based algorithms, natural language processing (NLP) for text data, and machine learning models for pattern recognition, were used to automate and improve the extraction process. This step was referred to as the pre-processing stage, which assists in identifying key characteristics that may impact subsequent analysis.

(c) Resiliency-Sustainability Level Calculation:

In the second step, the system calculated the resiliency-sustainability level of the supplier using two primary metrics: the fulfillment rate and the Triple Bottom Line performance.

1. The resiliency level was calculated using Equation 1:

    Resiliency Level = (Fulfilled Orders / Total Orders) × 100

2. The sustainability level was determined using the TBL method, which evaluates the supplier's performance across three dimensions: economic, environmental, and social. The calculation Equation 2 is as follows:

    Sustainability Level = (Economic Performance + Environmental Performance + Social Performance) / 3

- Economic KPIs: Measures related to cost efficiency, financial stability, and overall economic impact of the supplier.
- Environmental KPIs: Metrics assessing the supplier's environmental practices, such as waste reduction, energy efficiency, and carbon footprint.
- Social KPIs: Indicators reflecting the supplier's social responsibility, including labor practices, community engagement, and ethical standards.

(d) Risk Analysis Using SCOR Model:

In the third step, the Supply Chain Operation Reference (SCOR) model was applied to assess supplier performance based on Key Performance Indicators (KPIs) such as reliability, responsiveness, agility, and sustainability. These KPIs were integrated with probabilistic risk assessment methods to calculate the probability of disruption occurrence for the supplier. This was done using Equation 3:

Equation 3. $R=P\times I$ where:

- R is the risk level,
- P is the probability of disruption, and
- I is the impact, which accounts for the supplier's resiliency and sustainability across economic, environmental, and social dimensions.

The SCOR model is applied as follows:

- Reliability: Measured by analyzing historical delivery data to determine the supplier's ability to deliver orders on time and in full.
- Responsiveness: Evaluated by calculating the supplier's lead time and their ability to respond to urgent or dynamic order requirements.
- Agility: Assessed by measuring the supplier's flexibility to adapt to disruptions or sudden changes in demand.
- Sustainability: Analyzed based on metrics such as energy efficiency, carbon emissions, regulatory compliance, and waste management practices.

The probability of disruption (P) was calculated based on historical patterns of supplier performance and risk factors, while the impact (I) was derived by integrating the supplier's resiliency level and their sustainability performance across economic, environmental, and social dimensions. These values were combined in Equation 3 to calculate the overall risk level (R), providing a clear and quantifiable risk assessment for each supplier.

(e) Results Database Integration:

At this stage, all analysis reports were stored in the results database. When evaluating a new supplier, the system first checked whether the supplier’s analysis already exists in the database. The checks were performed as follows:

- The system queried the database using a unique supplier identifier, such as supplier ID, tax ID, or other relevant attributes, to determine if a corresponding analysis record was available.
- If a matching analysis existed, the system retrieved the data to avoid redundant calculations and directly uses the existing results for further decision-making.
- If no analysis was found, the system flagged the supplier as "new" and proceeds with a full analysis following the methodology described above. This automated checking process ensured efficiency, prevented duplication of effort, and maintains the integrity of the analysis workflow. The results database acted as a centralized repository, enabling seamless access to previously analyze data.

3. **Dynamic stages:** As illustrated in Figure 4.1, the dynamic stages of RSSSS 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, RSSSS entered a dynamic stage, during which we trained the machine learning algorithm on our data and subsequently model it using appropriate regression algorithms such as: Decision Tree, Random Forest, AdaBoost, Naive Bayes, K - Nearest Neighbors, Linear Discriminant Analysis, and XGBoost that are ordered through an open-source machine learning library Pandas, Scikit-learn. This stage contains three main steps:

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

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

iii. Supplier Resiliency-Sustainable Level: The system was ready to generate a resiliency-sustainable level for every supplier. The generated resiliency-sustainable level indicated whether supplier resilient-sustainable or not.

(b) Fifth, in this stage, RSSSS validates the results to determine if the supplier was resilient-sustainable, which indicated a low risk on its process of supplying the manufacturer, or not resilient-sustainable, which indicated a high risk on its process of supplying the manufacturer, respectively. As the last phase of this stage, the system reported to the manufacturer the level of supplier resilience-sustainability and provided a detailed explanation of supplier weaknesses.

CHAPTER FOUR

RESULTS AND ANALYSIS

This chapter presents a comprehensive account of the empirical results obtained from implementing the Resilient-Sustainable Supplier Selection System (RSSSS). It provides a detailed description of the tools and methods employed, including dataset preparation, model training, and the comparative evaluation of different machine learning algorithms. All results reported in this chapter are derived from the empirical analysis conducted using Python, implemented in a Google Colab environment.

Tools and Techniques

The RSSSS framework was designed and evaluated using a combination of data analysis tools, programming environments, and supervised machine learning workflows. The coordinated use of these resources ensured correct model implementation, efficient computation, and full reproducibility of the empirical results.

Development Environment

All experiments were implemented in Google Colab, a cloud-based notebook environment that supports Python. Google Colab was chosen because of its user-friendly interface, seamless integration with major machine learning libraries, and access to GPU/TPU resources for faster computation. It provided a flexible and interactive setting for executing code cells, analyzing results, and visualizing model performance comparisons.

Programming Language

All code was written in Python, a versatile programming language widely used in data science and artificial intelligence research. Python was selected because of its rich ecosystem of open-source libraries, concise and readable syntax, and strong compatibility with various machine learning frameworks. In addition, its scalability and extensive community support made it well suited for iterative experimentation and large-scale data processing in this study.

Libraries and Frameworks

Several Python libraries and frameworks were used throughout the development and evaluation of the models. These tools played a critical role in key tasks such as data preprocessing, model training, and performance visualization. They also supported efficient workflow management, high computational throughput, and reproducibility of results across multiple experimental runs.

Table 6 *Libraries and Frameworks Used in RSSSS Implementation*

Library / Framework	Purpose in Implementation
Pandas	Used for data cleaning, feature selection, and transformation of supplier records.
NumPy	Performed efficient numerical operations and array manipulations during data preprocessing.
Scikit-learn (sklearn)	Provided machine learning algorithms (Decision Tree, Random Forest, K-NN, LDA, Naive Bayes, AdaBoost) and preprocessing tools.
Joblib	Used to save and reload trained models and encoders for future use.
Matplotlib	Created visualizations such as accuracy comparisons, supplier distributions, and training time charts.

Table 6 summarizes the main Python libraries and frameworks used in the implementation of the RSSSS, along with their specific roles in data preprocessing, model training, and result visualization.

Machine Learning Techniques

In this study, supervised machine learning techniques were employed to classify suppliers as resilient-sustainable and to compare their performance within the RSSSS framework. All models were trained and evaluated on the same dataset to ensure a fair and consistent comparison of their predictive capabilities[111]. The following algorithms were implemented:

Decision Tree (DT): A hierarchical model that recursively splits the data into decision nodes based on feature values, producing an interpretable tree structure for classification.

Random Forest (RF): An ensemble method that aggregates the predictions of multiple decision trees to improve accuracy and reduce overfitting.

AdaBoost (AB): A boosting algorithm that iteratively combines several weak learners, adjusting their weights to minimize classification errors and improve overall performance.

Naive Bayes (NB): A probabilistic classifier based on Bayes' theorem that assumes conditional independence between features, offering a simple and fast baseline model.

k-Nearest Neighbors (k-NN): A distance-based classifier that assigns a class to a new instance based on the majority class among its k closest neighbors in the feature space.

Linear Discriminant Analysis (LDA): A linear classification technique that projects feature onto a lower-dimensional space to maximize class separability.

XGBoost (XGB): A high-performance gradient boosting algorithm that builds an ensemble of decision trees sequentially, focusing on minimizing prediction errors and achieving high classification accuracy.

Evaluation Metrics

To evaluate the performance of all models in the RSSSS, two primary metrics were used:

Accuracy (%): The proportion of correctly classified supplier instances.

Training Time (seconds): The total time required to train each model, reflecting its computational performance.

Together, these metrics capture the trade-off between predictive performance and computational efficiency and provide a common basis for comparing the different machine learning algorithms.

***Table** 7 Evaluation Metrics Used.*

Metric	Description	Purpose
Accuracy	Percentage of correct supplier classifications.	Determines the predictive reliability of each model.
Training Time	Total computation time required for model training.	Measures computational efficiency and scalability of each model.

Data Summary and Preprocessing

The dataset used in this study consisted of historical supplier data capturing operational, geographical, and logistical characteristics [112]. After preprocessing, including the removal of redundant columns, encoding of categorical variables, and handling of missing values, the final dataset comprised 74,339 observations and 13 key features. These features represented indicators of supplier reliability, agility, geographical location, and sustainability-related attributes.

Table 8 *Final Dataset Features Used*

No.	Feature Name	Description
1	Location	Geographic location associated with the supplier or distribution point.
2	Supplier	Encoded identifier representing individual suppliers.
3	Agility	Indicator of the supplier's ability to respond to changes and disruptions.
4	Incoming Quantity	Quantity of goods received from the supplier.
5	Purchase Order Quantity	Quantity specified in the purchase order.
6	Delivery Lead Time	Time elapsed between order placement and delivery.
7	Distance	Physical distance between the supplier and the destination.
8	Delivery Method	Mode of transportation used for shipment (encoded categorical variable).
9	Capability	Supplier's operational and production capability level.
10	Order Country	Country in which the purchase order was placed.
11	Order Date	Date on which the purchase order was issued.
12	Shipping Date	Date on which the order was shipped.
13	Derived Time Feature	Engineered temporal feature capturing time-based differences (e.g., order-to-shipment duration).

Table 8 presents the final set of features retained after data preprocessing. These features represent key supplier, order, and logistics characteristics relevant to assessing supplier resilience and sustainability. All variables were encoded, cleaned, and processed to address missing values before being used as input features for training the machine learning models.

To ensure a balanced representation of supplier classes, the 10 most prominent suppliers were selected for model training and validation. This sampling strategy supported efficient computation and helped mitigate potential class imbalance issues. The resulting dataset was then split into 80% for training and 20% for validation and testing, providing a robust basis for evaluating the performance of the machine learning models within the RSSSS framework.

Figure 8 *Distribution of Top 10 Suppliers in the Dataset*

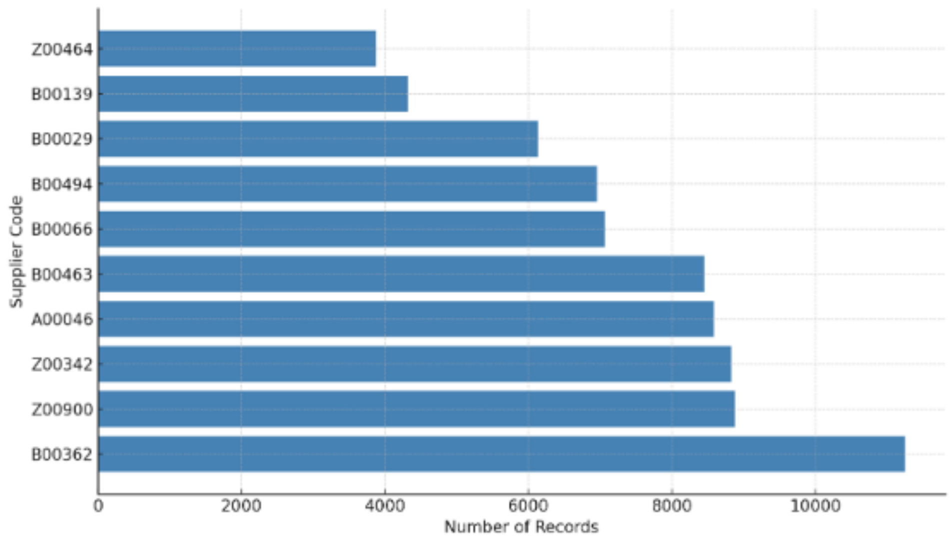


Figure 8 illustrates the frequency of records associated with the ten most represented suppliers. As shown in the figure, supplier B00362 has the highest number of records (11,251), followed by Z00900 (8,882) and Z00342 (8,828). The substantial number of observations for these suppliers provides a sufficient data basis for training and validating the machine learning models within the RSSSS framework.

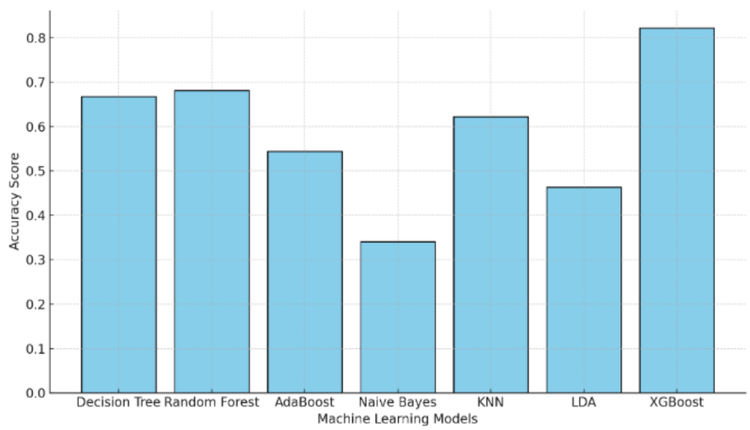
Model Evaluation and Performance Metrics

The seven supervised machine learning models were trained and evaluated on the same supplier dataset. Their performance was assessed using two metrics: classification accuracy and training time. The Python implementation produced the results summarized in Table 9.

Table 9 *Performance Comparison of Machine Learning Models*

Model	Accuracy (%)	Training Time (s)
Decision Tree	66.79	0.38
Random Forest	68.09	4.66
AdaBoost	54.37	2.67
Naive Bayes	34.07	0.03
K-Nearest Neighbors (KNN)	62.18	0.28
Linear Discriminant Analysis (LDA)	46.37	0.09
XGBoost	**82.23**	**5.96**

Figure 9 *Model Accuracy Comparison for Supplier Classification*



As shown in Table 9 and Figure 9 XGBoost achieved the highest classification accuracy at 82.23%, outperforming all other models. Random Forest and Decision Tree followed with accuracies of 68.09% and 66.79%, respectively. Naive Bayes produced the lowest accuracy (34.07%), which is likely due to its strong independence assumption between features, an assumption that does not hold in a multidimensional resilience-sustainability context. Overall, these results indicate that more advanced, tree-based ensemble methods (Random Forest and especially XGBoost) are better suited to capturing the complex, non-linear relationships between supplier resilience and sustainability indicators than simpler linear or probabilistic models.

Comparative Analysis of Computational Efficiency

In addition to classification performance, the training time of each model was recorded to assess computational efficiency. As shown in Table 9, XGBoost required the longest training time (5.96 seconds) but also achieved the highest accuracy. This trade-off between predictive performance and computational cost suggests that XGBoost is particularly well suited for precision-intensive supplier assessment tasks, where accuracy is prioritized over minimal computation time. By contrast, Naive Bayes, and Linear Discriminant Analysis (LDA) trained in a fraction of a second but delivered substantially lower classification accuracies**.** Meanwhile, Random Forest required 4.66 seconds to train and offered a reasonable balance between accuracy and computational cost, making it a viable option for deployment in medium-scale enterprise environments.

Figure 10 *Model Accuracy vs Training Time Comparison*

Figure 10 presents a two-axis chart that contrasts model accuracy against training time, visually illustrating the efficiency trade-off between predictive performance and computational complexity. The figure reinforces the robustness of XGBoost as the most accurate model and highlights the practical feasibility of Random Forest as a compromise between speed and performance.

Summary of Chapter

This chapter presented the tools, data structure, and empirical results obtained from the implementation of the RSSSS model. The dataset consists of 74,339 supplier records with 13 predictive variables related to operational, resilience, and sustainability characteristics. Notably, XGBoost achieved the highest classification accuracy of 82.23%, making it the most suitable model for supplier classification within the RSSSS framework. Random Forest and Decision Tree delivered competitive accuracy with moderate computational requirements, offering viable alternatives when a balance between performance and efficiency is needed. Naive Bayes and LDA were considerably less effective, likely because their underlying assumptions do not capture the complex interactions among supplier characteristics. These empirical results form the basis for the interpretation and critical discussion presented in Chapter 5.

CHAPTER FIVE

DISCUSSION

Introduction

This chapter discusses the empirical findings of the proposed Resilient-Sustainable Supplier Selection System (RSSSS) in relation to the research objectives, research problem, and hypotheses. It explains how the machine learning (ML) models performed, how the integration of resilience and sustainability added value to supplier selection, and what these results mean for small and medium-sized enterprises (SMEs). The chapter is organized around the three hypotheses (H1, H2, H3), followed by a discussion of the theoretical and practical implications, the limitations of the study, and possible directions for future research.

Machine Learning Performance and Validation of H1

Several previous studies have demonstrated the effectiveness of machine learning in supplier evaluation and risk assessment. For example, one study applied Random Forest and Support Vector Machines (SVM) to simulated supply chain data to analyze and predict supplier-related risks, thereby enhancing data-driven risk and sustainability assessment [30]. Similarly, [108] developed machine learning based classification models using a Multilayer Perceptron (MLP) to group suppliers into efficient and inefficient categories, showing that machine learning techniques can support practical supplier selection decisions. More recently, [109] proposed a hybrid machine learning based Resilient Supplier Selection System (RSSS) that accurately classified resilient versus non-resilient suppliers using historical data and behavioral risk indicators. However, these studies primarily focused on efficiency or resilience in isolation and do not explicitly address the joint prediction of resilient-sustainable suppliers using a comprehensive set of resilience and sustainability features, as undertaken in the present research.

The empirical results presented in Chapter Four provide strong support for H1. Among the seven machine learning models evaluated, XGBoost achieved the highest classification accuracy of 82.23%, clearly outperforming the alternative models trained on the same supplier dataset. This result confirms that machine learning algorithms can accurately predict resilient-sustainable suppliers based on historical operational, resilience, and sustainability data. The superior performance of XGBoost indicates that advanced ensemble methods are well suited to capturing the complex relationships inherent in supplier evaluation tasks.

In contrast, simpler models such as Naive Bayes and Linear Discriminant Analysis (LDA), exhibited substantially lower classification accuracies of 34.07% and 46.37%, respectively. These weaker results can be explained by the strong assumptions underlying these techniques. Naive Bayes assumes statistical independence among features, while LDA assumes linear separability between classes. In the context of supplier evaluation, resilience, and sustainability indicators, such as reliability, agility, geographic diversification, and sustainability, related attributes are highly interdependent and interact in non-linear ways. As a result, these models are unable to adequately represent the underlying data structure and therefore perform poorly.

Moderate performance was observed for K-Nearest Neighbors (k-NN), Decision Tree, and Random Forest models, which achieved accuracies of 62.18%, 66.79%, and 68.09%, respectively. These results suggest that models capable of handling non-linear relationships generally outperform purely linear or probabilistic approaches. Nevertheless, the performance gap between these models and XGBoost highlights the advantage of gradient-boosting ensemble techniques, which combine multiple weak learners into a more robust predictive model.

Overall, the comparative analysis of the seven models demonstrates that machine learning, and in particular tree-based ensemble methods such as XGBoost, can effectively learn from historical supplier data to identify resilient-sustainable suppliers. This finding confirms the central claim of H1 and supports the broader premise of the RSSSS: that intelligent, data-driven approaches provide more accurate and reliable supplier classifications than traditional rule-based or cost-focused evaluation methods.

In summary, the validation of H1 is consistent with earlier studies that applied machine learning to supplier evaluation and risk profiling [30], as well as with research demonstrating the effectiveness of neural networks and hybrid machine learning frameworks in classifying supplier performance [108][109]. However, the present study extends this body of knowledge by evaluating multiple machine learning algorithms on a large, real-world dataset and by explicitly framing the prediction task around resilient-sustainable suppliers rather than efficiency or resilience alone. This finding positions the RSSSS as a more integrated and sustainability aware machine learning based decision support system, particularly suited to the needs of small and medium-sized enterprises.

Performance of RSSSS Compared with Traditional Supplier Selection Approaches (H2)

Several prior studies have attempted to enhance supplier selection by combining multi-criteria decision-making (MCDM) with intelligent or data-driven techniques. For instance, one study proposed an integrated MCDM-machine learning model to improve the reliability of supplier evaluation in the automotive industry; however, the approach did not explicitly address the needs of small and medium-sized enterprises (SMEs) or support real-time decision-making [73]. Similarly, fuzzy MCDM frameworks have been developed to merge resilience and sustainability criteria under uncertainty, yet these methods remain largely static and do not leverage advanced machine learning models capable of learning from large-scale historical data [76]. In addition, [109] introduced a hybrid machine learning based Resilient Supplier Selection System (RSSS) that improved resilience-oriented classification but did not fully integrate sustainability metrics or provide a comprehensive, SME-focused decision support solution. Against this background, Hypothesis 2 examines whether the proposed Resilient-Sustainable Supplier Selection System (RSSSS) can outperform traditional and MCDM-based approaches in terms of predictive accuracy, evaluation speed, and comprehensiveness.

The empirical results presented in Chapter Four provide strong support for H2. In terms of predictive accuracy, the RSSSS, built on the best-performing machine learning model, XGBoost achieved an accuracy of 82.23%, which is substantially higher than what is typically expected from traditional rule-based or cost-focused supplier selection methods. Conventional approaches often rely on weighted scoring of a limited set of criteria, such as cost, quality, and delivery time. In contrast, the RSSSS incorporates a richer and more diverse feature set that includes operational, resilience, and sustainability indicators. This multidimensional representation, combined with machine learning's ability to capture complex non-linear relationships, enables more precise identification of resilient-sustainable suppliers.

With respect to evaluation speed and computational efficiency, the results indicate that the XGBoost model required 5.96 seconds to train on a dataset of 74,339 supplier records with 13 features. Once trained, the model can classify new suppliers almost instantaneously. Compared with manual, spreadsheet-based, or expert-driven evaluation processes, where decision-makers must review multiple performance reports, ESG disclosures, and operational records, the automated RSSSS significantly reduces the time required to generate supplier risk profiles and rankings. Alternative models such as Random Forest and Decision Tree also demonstrated relatively short training times, offering viable options when a balance between accuracy and computational cost is required.

The comprehensiveness of the RSSSS further distinguishes it from conventional supplier selection practices. Rather than treating resilience and sustainability as secondary or separate considerations, the system integrates both dimensions into a unified classification and ranking framework. Doing so allows decision-makers to simultaneously evaluate cost-related factors, resilience indicators (such as agility, reliability, and geographic diversification), and sustainability-related attributes (including environmental and operational performance) within a single decision support environment.

When coupled, these findings confirm H2: the RSSSS not only delivers higher predictive accuracy than traditional supplier selection approaches but also improves evaluation speed and provides a more comprehensive assessment of suppliers. For SMEs, this represents a practical, machine learning-enabled alternative to fragmented, manual, and often subjective evaluation processes, supporting more consistent and risk-aware sourcing decisions.

Overall, the validation of H2 is consistent with prior research that sought to enhance supplier selection reliability using MCDM and AI-based methods [73], [76]. However, the RSSSS advances this line of work by leveraging a high-performing machine learning algorithm on a large historical dataset to deliver fast, automated, and multidimensional evaluations. Compared with hybrid machine learning frameworks that focus primarily on resilience, such as the RSSS approach proposed by [109], the RSSSS explicitly integrates both resilience and sustainability criteria and is implemented in a lightweight environment suitable for SMEs. This approach positions the RSSSS as a more comprehensive and practically deployable decision support system than many existing approaches in literature.

Sustainability-Resilience Integration and Supply Chain Risk (H3)

Several studies in the literature have explored the relationship between resilience and sustainability in supplier selection and supply chain design. For example, one stream of research proposed fuzzy multi-criteria decision-making (MCDM) frameworks that merge sustainability and resilience criteria, demonstrating that both dimensions can be considered jointly within a multi-criteria evaluation setting [76]. Another inquiry employed artificial intelligence and resilience-oriented modeling to examine how AI can strengthen supply chains in the post COVID-19 context; however, these studies did not develop a concrete, data-driven supplier selection model that explicitly integrates sustainability indicators [75]. In addition, simulation-based and machine learning driven approaches have been introduced to support resilient supplier selection in digital manufacturing environments [78], yet sustainability is often treated as a separate or secondary concern rather than as a fully integrated component of the evaluation process. Against this background, Hypothesis 3 examined whether integrating sustainability metrics directly into the machine learning based RSSSS can strengthen overall supply chain resilience and reduce risk for small and medium-sized enterprises (SMEs).

The empirical results and supplier classification outcomes generated by the RSSSS provide meaningful support for H3. By embedding sustainability-related variables alongside operational and resilience indicators in the model's feature set, the RSSSS demonstrates that sustainability metrics contribute directly to identifying suppliers with stronger resilience profiles. The strong classification performance of tree-based models suggests that sustainability attributes are not merely supplementary criteria but form an integral part of the underlying patterns that distinguish resilient-sustainable suppliers from higher-risk alternatives.

From a risk management perspective, the integration of sustainability metrics enables SMEs to identify suppliers that are less exposed to long-term operational, regulatory, and reputational risks. Suppliers with weaker sustainability performance are more likely to face environmental incidents, regulatory sanctions, or governance-related disruptions, which can ultimately translate into supply chain interruptions. By incorporating sustainability indicators into the RSSSS, decision-makers are encouraged to favor suppliers whose practices support both short-term operational continuity and long-term supply chain stability.

Combined, the support for H3 complements earlier conceptual and MCDM-based studies that argue for integrating sustainability and resilience in supplier selection [75], [76], while extending this literature in an important way: whereas prior research often relies on fuzzy logic or policy-oriented frameworks that lack adaptive learning capabilities, the RSSSS embeds sustainability metrics directly into a supervised machine learning framework that simultaneously captures resilience-related attributes. Doing so enables SMEs not only to recognize the theoretical link between sustainability and resilience, as highlighted in the literature, but also to operationalize this relationship through concrete, data-driven classifications and risk profiles that can be applied in day-to-day supplier selection and sourcing decisions.

Alignment with Research Objectives

Table 10 *Alignment of Research Findings with Research Objectives*

Research Objective	Supporting Discussion Evidence
1. Integrate resilience and sustainability in supplier evaluation	The empirical success of XGBoost confirms that joint modeling yields higher accuracy than separate analyses.
2. Develop a machine-learning-based risk-profiling framework	RSSSS delivers objective classifications with 82.23 % accuracy and measurable computational performance.
3. Classify and rank suppliers using ML algorithms	All seven models were benchmarked; XGBoost > RF > DT establish a robust ranking pipeline.
4. Provide a lightweight DSS for SMEs	Implementation in Python and Colab proves the framework's accessibility and scalability.
5. Deliver transparent, data-driven insight into supplier risk	Comparative metrics and visualization enable objective monitoring free of expert bias.

Table 10 demonstrates clear alignment between the study's empirical outcomes and the stated research objectives. First, the strong performance of the best model (XGBoost) supports the objective of integrating resilience and sustainability within a single supplier evaluation framework, indicating that joint modeling can improve predictive capability compared with treating these dimensions separately. Second, the RSSSS operationalizes a machine learning, based risk-profiling framework by producing objective supplier classifications with 82.23% accuracy and documented computational efficiency, strengthening the system's validity and repeatability. Third, the benchmarking of seven algorithms establishes a structured classification and ranking pipeline, where the comparative performance pattern (XGBoost > Random Forest > Decision Tree) provides evidence that the system can reliably prioritize suppliers based on resilience-sustainability profiles. Fourth, implementation using Python and Google Colab confirms the feasibility of delivering a lightweight and accessible DSS suitable for SMEs, supporting scalability without heavy infrastructure requirements. Finally, by reporting comparative metrics and enabling visual performance monitoring, the system provides transparent, data-driven insight into supplier risk and sustainability performance, reducing reliance on subjective judgment and helping decision-makers identify supplier strengths and weaknesses in a consistent manner.

Theoretical Implications

Existing studies have explored different aspects of supplier selection, resilience, and sustainability, but often they go about doing so in a fragmented way. Some works have used machine learning to analyze supplier risk and performance without explicitly integrating both resilience and sustainability dimensions in a unified model [30], while others have focused on fuzzy MCDM frameworks to combine resilience and sustainability criteria conceptually, but without leveraging advanced data-driven learning techniques [76]. In addition, hybrid ML-based systems have been proposed to support resilient supplier selection, particularly in SME-related contexts, yet these models typically emphasize resilience or risk profiling alone and do not fully integrate sustainability indicators into their decision logic [109]. With this in mind, this dissertation offers several theoretical implications that extend and connect these strands of research.

In particular, the findings have several theoretical implications for the fields of supplier selection, supply chain resilience, and sustainability. First, the research provides a concrete operationalization of the often-theoretical link between resilience and sustainability in supplier evaluation. While prior studies frequently discuss these concepts separately, the RSSSS demonstrates that they can be jointly embedded into a single, data-driven decision framework. By integrating resilience and sustainability indicators into the feature set used for classification, this study supported the view that these dimensions are complementary rather than competing and should be treated as interconnected constructs in supply chain theory.

Second, the study advances the theoretical understanding of how machine learning can be used in supplier selection. It showed that tree-based ensemble methods, particularly XGBoost, are capable of modelling the complex, non-linear interactions among operational, resilience, and sustainability attributes. This challenges traditional linear and multi-criteria models that assume simple additive effects and suggests that more sophisticated learning-based approaches can capture richer patterns in supplier behavior and risk.

Third, the research contributes to the literature on SME-oriented decision support systems by demonstrating that advanced ML techniques can be implemented in a lightweight, practical way using accessible tools (such as Python and Google Colab). This positions ML-based supplier selection not only as a concept for large corporations, but as a viable solution for SMEs, and thus extends the theoretical discussion on digitalization and analytics in smaller firms.

Finally, by linking empirical model performance (e.g., accuracy and training time) with conceptual constructs (resilience, sustainability, and risk), the study helps bridge the gap between abstract supply chain concepts and operational decision tools, demonstrating that theoretical ideas can be translated into measurable, algorithmic evaluations of suppliers.

Practical and Managerial Implications for SMEs

Many existing studies acknowledge that advanced decision models and AI-based systems can improve supplier selection, but they often remain difficult for SMEs to adopt in practice. For example, some works propose MCDM and big data-based multi-agent systems to support supplier selection in large or data-rich environments, without fully addressing the resource and capability constraints of smaller firms [73], [79]. Likewise, hybrid ML frameworks for resilient supplier selection, such as the RSSS developed by [109], focus mainly on resilience and risk profiling, and do not explicitly provide a lightweight, sustainability-integrated decision support solution tailored to SMEs. In this context, the practical and managerial implications of the RSSSS in this study are particularly relevant for SME contexts.

The results of this study have important practical implications for small and medium-sized enterprises (SMEs), too, particularly those operating in uncertain and risk-prone supply chain environments. First, the RSSSS provides a practical, data-driven tool that helps SMEs move beyond traditional, cost-only supplier selection practices. Instead of relying primarily on unit price, basic quality checks, or informal judgements, decision-makers can use the system to obtain an objective classification of suppliers based on resilience and sustainability criteria. This capability supports more structured and transparent decision-making and reduces the risk of selecting suppliers that may be cheap in the short term but vulnerable or unsustainable in the long term.

Second, the system's ability to generate supplier rankings and risk profiles gives managers actionable insight into their supply base. SMEs can:

- Identify high-performing resilient-sustainable suppliers for long-term strategic partnerships.
- Detect high-risk suppliers that may require closer monitoring, contingency planning, or substitution.
- Segment suppliers according to their resilience and sustainability performance, enabling differentiated contracting, collaboration, and improvement initiatives.

Third, the relatively modest computational requirements of the best-performing models (especially Random Forest and Decision Tree) and the implementation of the system in Python and Google Colab mean that RSSSS can be adopted without heavy investment in IT infrastructure. This cost effectiveness makes ML-based supplier evaluation more accessible to SMEs, which often lack dedicated data science teams or advanced analytics platforms.

Finally, by explicitly incorporating sustainability metrics alongside resilience and operational indicators, the RSSSS helps SMEs align their procurement decisions with broader environmental, social, and governance (ESG) expectations. This alignment can support compliance with emerging regulations, improve corporate reputation, and strengthen relationships with customers and stakeholders who increasingly prioritize sustainable and resilient supply chains.

Limitations of the Study

Despite its contributions, this study has limitations that should be acknowledged when interpreting the findings. First, the empirical analysis is based on a single supplier dataset comprising 74,339 records and 13 features. Although this dataset is sufficiently large for robust model training and evaluation, its structure and characteristics may reflect a specific industry context, data source, or regional setting. As a result, the generalizability of the RSSSS to other sectors, supply chain structures, or geographical regions may be limited without further validation.

Second, the quality of the model outputs is dependent on the quality of the input data. Any noise, bias, missing information, or inaccuracies in the underlying supplier records will influence the model's predictions. In particular, if some resilience or sustainability-related attributes are self-reported by suppliers or not regularly updated, the resulting classifications may not fully reflect current performance or risk levels.

Third, the study focused on supervised learning using historical data. The models were trained on past records and assumed that historical patterns are informative of future behavior. While this is a common and practical assumption, it may not fully capture abrupt structural changes in the supply chain environment or emerging risks that are not yet reflected in the historical data. The current implementation does not incorporate real-time data streams (e.g., IoT sensor data, logistics tracking, or social media sentiment), which could enhance the timeliness and responsiveness of the RSSSS.

Fourth, the evaluation primarily relies on accuracy and training time as performance metrics. Although these measures are useful and intuitive, they do not capture all aspects of model performance. For example, the study does not explicitly analyze precision, recall, F1-score, or the cost of misclassification for different supplier categories, which may be important for certain managerial contexts where false positives or false negatives carry different risks.

Finally, the interpretability of some models, especially ensemble methods such as XGBoost, remains limited in the current implementation. While the study demonstrated their predictive strength, it did not deeply explore explainable AI (XAI) techniques to make individual predictions more transparent to decision-makers, which is particularly relevant when sustainability and regulatory compliance are involved. These limitations provide important context for the findings and point to several opportunities for future research and system enhancement.

Summary

This chapter interpreted the empirical results of the RSSSS in light of the research objectives and hypotheses. It showed that ML algorithms, especially XGBoost, can accurately classify resilient-sustainable suppliers (H1), that the RSSSS outperforms traditional supplier selection practices in several key aspects (H2), and that integrating sustainability metrics supports a more resilient and less risky supply chain for SMEs (H3). The chapter also highlighted the theoretical contributions of the study, outlined practical implications for SMEs, and discussed key limitations. These points together prepare the ground for the final conclusions and overall contributions of this dissertation, which follow in Chapter Six.

CHAPTER SIX

CONCLUSION AND FUTURE WORK

Conclusion

The current research was to develop and test a system of Resilient Sustainable Supplier Selection System (RSSSS) based on machine-learning algorithms, and the purpose of the research was to improve the accuracy and objectivity of supplier selection processes. The framework used a dataset that comprised of 74,339 supplier records and 13 salient attributes that relates to operational, logistical and sustainability variables. Using and evaluating seven monitored learning algorithms such as Decision Tree, Random Forest, AdaBoost, Naive Bayes, K -Nearest Neighbors, Linear Discriminant Analysis, and XGBoost, the analysis provided an empirical evaluation of each of the models in promoting sustainable and resilient supplier classification.

The experimental findings revealed that the XGBoost model recorded the best classification accuracy of 82.23, which was best among all other considered algorithms. This observation confirms the appropriateness of ensemble-based learning to the modelling of complex supplier behaviors and interdependences among characteristics of delivery reliability, geographic dispersion, and sustainability measures. Conversely, conventional models such as Naive Bayes and Linear Discriminant Analysis, had low performance, which is mainly due to their simplifying assumptions on data linearity and independence.

In terms of practicality, the RSSSS framework shows that machine learning has the ability to automate the process of evaluating suppliers by replacing manual and subjective decision-making with objective and data-driven classification. The system reduces the use of expert judgement or pair-wise weighting schemes that is typical of traditional multi-criteria decision-making (MCDM) techniques. In addition, due to the open-source nature of its implementation (Python, Scikit-learn, XGBoost, Google Colab), it is economical, and scalable. Moreover, it can be used by small and medium-sized enterprises (SMEs) that have limited resources but still need powerful decision-support mechanisms.

The suggested system makes significant contributions when compared to the state-of-the-art studies. The RSSSS model is not based on extensive expert intervention and subjective marking as in the case of fuzzy models or hybrid MCDM-ML model; thus, it is quite reliable and consistent in its outcomes and is repeatable. Moreover, the model is flexible, and retraining is possible when new information on suppliers is available, which contributes to the dynamic decision-making in changing supply-chain environments.

Future Work

Although the RSSSS framework shows great potential, there are a number of opportunities to further improve, expand, and connect it with the new technologies. The current findings may be extended to the future research as follows. To start, the existing data is restricted to top 10 suppliers to one organizational setting. To achieve the cross-domain generalization, an increase in the size of the data should include several firms, industries, and geographical locations and would enhance the strength of the classification model. The multi-sector datasets would be able to represent a wider range of supplier behaviors, risk factors, and sustainability practices that are characteristic of global supply chains.

Secondly, the model is highly accurate, but it is narrow in that it focuses on operational and logistical aspects. Future iterations must include the metrics of environmental, social, and governance (ESG), such as carbon emissions, ethical sourcing, labor practices, and resource efficiency, in order to be consistent with Triple Bottom Line (TBL) vision of sustainability research [80]. The ESG variables would be included, thereby strengthening the sustainability aspect and offering a better evaluation structure of suppliers.

Thirdly, model interpretability and transparency ought to be of significance in future studies. Such approaches as SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-Agnostic Explanations) might be used to visualize feature significance and explain the logic behind the separation of certain suppliers. Greater transparency would make the RSSSS framework more reliable to decision-makers and especially in industries where the level of regulatory compliance is high.

Fourthly, a hybrid ML-MCDM model has potential benefits, should it be developed. The framework would be able to combine the predictive power of the XGBoost with the structured interpretability of the MCDM methods (e.g., TOPSIS or SWARA) to create objective, data-driven scores to be processed by a ranking or weighting methodology, thus balancing the power of quantitative prediction and the human-guided interpretive capability.

Other than the above mentioned, it is also possible to extend the framework with real-time analytics by integrating cloud-based models or Internet of Things Internet of Things (IoT) connectivity, which allows automated supplier status notifications and early-warnings about disruptions to the supply-chain. The integration of blockchain technology may also add more transparency and traceability of the supplier information to create a safe ecosystem of sustainable procurement.

Lastly, a deep-learning-based solution, such as Graph Neural Networks or Long Short-Term Memory (LSTM) networks, can potentially be used to model the time-series supplier performance data, which includes time-dependent dependencies and predicts the resilience under uncertain or dynamic market conditions.

In sum, although this study provides a solid base, the next phases of the study are to increase the scope of the model (10-15 domains validation), depth (ESG integration), and explainability (explainable AI). These innovations will make the RSSSS framework a technically accomplished classification system to a strategic, transparent, and ethically sound decision support system of resilient and sustainable supply chains in the future.

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