



A Hybrid Approach Based on Data Density Analysis for Group Supplier Selection Problem Considering Multi-Level Risk Assessment: A Case Study

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Article Info

Article type:
Research Article

Article history:

Received 27 May 2026
Received in revised form 20 June 2026
Accepted 17 September 2026
Available online 30 September 2026

Keywords:

supplier selection,
risk-based clustering,
fuzzy delphi,
best-worst method (BWM)

ABSTRACT

Supplier selection can be considered as the most important activity in the purchase process, as it significantly affects the organization. Despite the presence of powerful suppliers, a variety of risks can be imagined as being encountered by organizations. Therefore, it is necessary to identify the related risks, and important decisions should be made by the organization regarding suppliers with different levels of risks. The problem under consideration, is the group suppliers selection based on different levels of related risk criteria. The multi-stage method begins with identifying the risk and after identifying the final risk criteria, the weights of the criteria are determined using the BWM method. A weighted matrix based on the identified quantitative and qualitative risks, commensurate with supplier information and the weights of the criteria, is used as input to the DBSCAN clustering process. DBSCAN is an unsupervised approach and is used here for the supplier selection problem for the first time. We considered the Mega Motor Company, which is the largest manufacturer of powertrains in the Middle East and deals with hundreds of domestic and foreign suppliers. Clustering was performed for different values of ϵ and Minpts. The inter- and intra-cluster distances were used to evaluate the results and clustering quality. Then, the k-means method and unsupervised machine learning were used to assess the validity of the proposed approach. A comparison of inter- and intra-cluster distances of the two approaches verified the efficiency of the DBSCAN approach in dealing with the supplier selection problem.

Cite this article: Marjani, M.R. and et al. (2026). A Hybrid Approach Based on Data Density Analysis for Group Supplier Selection Problem Considering Multi-Level Risk Assessment: A Case Study. *Journal of Data Analytics and Intelligent Decision-Making (JDAID)*, 2(3), 1-30. <https://doi.org/10.22091/jdaid.2026.16147.1066>



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Publisher: University of Qom.

DOI: <https://doi.org/10.22091/jdaid.2026.16147.1066>

Introduction

Business companies attempt to reduce their costs. The costs of raw materials and components constitute the main production costs, and organizations should spend a large proportion of their earnings to purchase raw materials and parts (Maghsoodi et al., 2018). One of the most important activities in a supply chain is an effective purchase and logistics (Chou & Chang, 2008) that have strategic importance for the organization. Purchase costs contribute to a large share of organizational costs, and a company spends about 60% of its sales income on the purchase of raw materials and components (Krajewski, 2001). Thus, among the activities involved in the supply chain, decisions on the purchase greatly affect the overall system (Guo & Li, 2014). On the other hand, supplier selection can be considered the most important activity in the purchase performance, as it brings about significant savings for the organization (Haq & Kannan, 2006). Decision-making on supplier selection is one of the most crucial steps in supply chain management, and its importance in the success of the organization is undeniable. Choosing the appropriate supplier can increase the competence level within organizations and reduce the costs related to the purchase of materials and requirements as well as the delivery time (Pokharel, 2008).

Obviously, suppliers may cause some risks for the organization. It is necessary to identify associated risks to implement appropriate plans and reduce or eliminate associated undesirable effects. On the other hand, there are large companies that are communicating with hundreds of suppliers due to their performance domain to supply raw materials, requirements, components, montages, and other parts. In this regard, the importance of supply risk comes to the fore, and companies tend to select a group of suppliers rather than a single one.

A large number of researchers have addressed the importance of the group supplier selection (Ha & Krishnan, 2008; Haghighi et al., 2014; Heidarzade et al., 2016; Khaleie et al., 2012; Tricaud & Chen, 2010; Zhang et al., 2006). Various criteria for the supplier selection problem have been dealt with in previous studies, including qualitative and quantitative factors. Additionally, different methods have been proposed to select suppliers under uncertainty and risk, such as multi-criteria decision-making techniques, data envelopment analysis, linear programming, neural networks, fuzzy approaches, etc. (Azadeh & Alem, 2010; Boran et al., 2009; Vanany et al., 2009). It should be noted that, in cases where many suppliers are considered, the computational complexity is increased, and an approach such as data mining is required to turn data into useful information (Azadnia et al., 2011). Data mining, as an advanced capability, can be used to analyze such data and knowledge discovery. One of the critical methods of data mining is clustering, frequently employed for knowledge discovery and recognizing data patterns. Its capability to enter data space and understanding the data patterns turns clustering into one of the ideal mechanisms to work with massive data world. Indeed, this technique provides a classification of data in which data points in each cluster exhibit the greatest similarity to one another and the least similarity to those in other clusters.

As said, automobile manufacturers are dealing with hundreds of suppliers due to their working conditions. When a large number of suppliers are considered, the computational complexity is raised, and data mining techniques should be used to turn raw data into analyzable information. According to the above discussions, it is recommended to choose a group of

suppliers rather than a single supplier. The clustering of suppliers in terms of various characteristics provides some benefits (Er Kara & Firat, 2018) that are described in what follows.

- In recent years, numerous methods have been introduced for the supplier evaluation and selection problem. In such complex structures, it is highly difficult to find meaningful patterns. Clustering is a powerful tool to learn a set of complex and large information (Frank et al., 2016; Jain, 2010).
- Eliminating the supplier groups which lack specific information helps to obtain small and controllable supplier groups, reduce the number of alternatives, and increase the simplicity and flexibility of the supplier selection process (Bottani & Rizzi, 2008; Khaleie et al., 2012; Tricaud & Chen, 2010).
- This matter enables one to select a group of suppliers when the company prefers to choose more than one supplier due to some reasons such as suppliers' capacity constraints (Heidarzade et al., 2016).
- This approach helps to expedite the replacement of alternative suppliers in cases where an unpredictable lag in supplying raw materials occurs. Accordingly, the company can replace a failing supplier with a new one quickly to increase the productivity of the risk management process (Er Kara & Firat, 2018).
- This approach facilitates developing some specific plans and strategies for various groups of suppliers, increasing supplier relationship management, improving supplier performance management systems, and developing risk management systems effectively (Rezaei et al., 2015).

This research aims to analyze the relationship between the quality of shared data and risk management in the supply chain. In this regard, a function for measuring visibility based on the data quality dimensions has been defined, and the dimensions that are more significant in the downstream supply chain have been identified (Haghshenas Nasrabadi & Ghasemy Yaghin, 2025). This study aims to identify and rank the key barriers hindering the adoption of blockchain technology in the tourism industry, given its transformative potential and strategic relevance. The research utilized a mixed-method approach. First, the barriers were identified through a comprehensive literature review and expert interviews. A sample of 22 experts in Blockchain and tourism was selected, and data were collected using a structured questionnaire. The Interpretive Structural Modeling (ISM) technique was employed to prioritize the barriers, and Decision-Making Trial and Evaluation Laboratory (DEMATEL) method was used to analyze the causal relationships among them (Fathi et al., 2025). According to the above description, we propose a scientific approach to cluster suppliers based on their risk characteristics. To this end, we first review the relevant research to determine effective criteria related to suppliers and then share the criteria with the organization's experts to examine, validate and review them further. After determining and summarizing the criteria, the company's suppliers are identified, and information on each supplier regarding the criteria is gathered. Finally, the suppliers are classified using the density-based spatial clustering of applications with noise (DBSCAN) method to decide on them. Using this method, we can

classify suppliers in a scientific framework based on the associated risk criteria identified. Suppliers having high-risk characteristics can be removed, or some plans can be developed for suppliers based on the results of analyses.

In Section 2, a review of studies on identifying supplier risk and supplier selection approaches, such as individual or combinational ones, is provided. The risk criteria used in the supplier evaluation and selection process, as well as cluster analysis, is presented in Section 3. The model, research steps, and its results and the clustering algorithm are described in Section 4. Finally, Section 5 provides an analysis of the clustering results along with conclusion and recommendations.

Literature Review

In a competitive business environment, companies are seeking competitive advantage through data management and knowledge management. Supply chain management plays an important role in this issue. Supply chains have gained significant importance in the business world. Supplier selection is considered as a critical step in supply chain management (Senvar et al., 2014), and appropriate decision-making in this respect reduces purchase costs and provides a sustainable relationship with suppliers in the competitive market (Mohammadi Motlagh et al., 2015). Choosing appropriate suppliers to procure components is addressed as an important issue, and companies should maintain a strong and long-lasting relationship with suppliers to achieve their goals. Appropriate supplier selection leads to reducing operating costs, increasing profitability and product quality, and improving competence and quick response to customers' demands (Abdollahi et al., 2015).

Regarding the globalization of markets and increased competition, companies try to produce high-quality products or services (Chan & Kumar, 2007). In most American companies, the costs of raw material supply contribute to more than 40% of production costs (Liao & Rittscher, 2007). Nevertheless, the supplier selection problem is an issue related to large companies as well as academics (Wetzstein et al., 2019). Supplier selection is the process of finding the right supplier with the appropriate price and quality at the right time and quantity (Arabsheybani et al., 2018). In other words, supplier selection is a process for choosing some suppliers based on some risk criteria according to the company's conditions (Khaleie et al., 2012). The supplier selection problem is an important issue and considered one of the main steps in supply and purchase chains (Heidarzade et al., 2016; Junior et al., 2014; Wetzstein et al., 2016). Another research proposes a hybrid methodology using fuzzy multi-objective mixed integer linear programming model (FMOMILPM) to solve G-resilient multi-tier SS/OA problem within the uncertain demand and cost environment in food industry (Mohammed et al., 2023). Another study develops a comprehensive framework for evaluating sustainable suppliers in the textile industry, integrating Triple Bottom Line (TBL) principles with SWARA and TOPSIS methods. Initially, 20 sustainability criteria were identified through a rigorous review of the literature and expert consultations. These criteria were then limited to 15 key criteria based on expert evaluations using a 5-point Likert scale (Sithi et al., 2025). Another research study was conducted to select sustainable suppliers in the SC. Initially, a list of indicators for selecting sustainable suppliers was extracted, and these indicators were adjusted

and finalized using the fuzzy Delphi technique. Furthermore, the Step-wise Weight Assessment Ratio Analysis (SWARA) technique was used for weighting, and the Fuzzy Weighted Aggregates Sum-Product Assessment (F-WASPAS) technique was used for prioritizing suppliers (Rukhsar et al., 2025). This study examines how public manufacturing organizations select suppliers and contractors, highlighting the importance of setting clear evaluation criteria before making selections. Following the Iranian Public Procurement Regulations, a strong set of criteria was created for effective supplier assessment. A combined Multi-Criteria Decision-Making (MCDM) approach was employed, integrating the Fuzzy DEMATEL method to analyze relationships among selection criteria, and the Best-Worst Method (BWM) to assign weights, with the best and worst criteria derived from the results of the Fuzzy DEMATEL analysis (Kolour et al., 2026).

A Review of Supply Chain and Supplier Selection Risks

The quality of supplier selection and evaluation greatly depends on the choice of criteria (Kuo et al., 2015; Rezaei et al., 2016). Some qualitative and quantitative criteria have been introduced in the literature including costs, quality, delivery performance, production capabilities, research and development, and reputation (García et al., 2013; Nekooie et al., 2015; Paul, 2015; Wetzstein, 2016). Supplier evaluation criteria should be congruent to the company's requirements and applicable to the evaluation of all suppliers (Şahin & Supçiller, 2015). The importance of criteria is different depending on the target working priorities and strategies within the company (Govindan et al., 2015).

Supply chain risks are categorized into various types depending on the cause. The literature of supply chain risk management classifies risks into two types: operational risks and disruption risks (Torabi et al., 2015). According to Tang (2006), each event or accident disrupting the organization, such as an earthquake or terrorist attack, is called a disruption risk. Wildfires may also create persistent environmental contamination risks, as demonstrated by post-fire indoor pollution assessments (Goftari et al., 2026). In other words, operational risks are intrinsic and accompanied by uncertainty, such as supply and demand uncertainty that deters the operation. Indeed, disruption risks have a low occurrence probability and high impact, while operational risks have low to medium occurrence probability and low impact (Alikhani et al., 2019). According to Hu et al. (2010), the most frequently used criteria include quality, delivery, price/cost, production capability, services, management, technology, research and development, finance, flexibility, reputation, relationship, danger, safety, and environment. Chen et al. (2011) presented a list of some important criteria such as quality, delivery time, historical performance, guarantee and compensation, technological capability, geographical location, packaging ability, and communication system. Punniyamoorthy et al. (2011) applied 46 supplier selection criteria categorized into ten main criteria, including organization's management, quality, technical capability, production facilities and capacity, location, delivery, services, communication, safety, environment, and costs. They conducted a survey with 151 respondents to determine the relative weights of criteria.

Hamdi et al. (2018) reviewed 124 papers, authored from 2003 to 2014, related to supplier selection based on supply chain risk management. According to the review, the most

common risks include reliability risk, the variability of customer's request, risk of information sharing, and discount quantity. In another research, supply chain management risks were divided into purchase risk, production risk, sale risk, financial market risk, special risks related to the production network, political/legal risks, and other risks (Häntsch & Huchzermeier, 2013). Er Kara and Firat (2018) sought to identify risk factors by reviewing the relevant literature. Then, they identified the final risk criteria for supplier selection by conducting some interviews and periodic meetings with managers. They identified 17 risk criteria and classified them into eight classes. The risk criteria included supplier's prior performance, changes in product prices, financial conditions, percentage outsourced work by the supplier, production capability, flexibility, technological capabilities, supplier's average damage rate, quality management attempts, delivery delay rate, changes in the sending time, packaging quality and transportation, communication convenience, reliability, problem-solving performance, guarantees, after-sales services, and catastrophe planning to face disruption.

Alikhani et al. (2019) tried to identify risk criteria by a review of the literature and interviews with experts. They identified ten criteria including quality, cost, long-time cooperation, bankruptcy, on-time delivery, finance constraints, supplier specifications, persistence and continuity, second level and contracting supplier, and opportunism.

Table 1. A Review of Relevant Literature

Approach	Author	Year	Research Methods	Group Suppliers	Risk Criteria	Cluster Analysis	DBCM*	Case Study
	Wu et al.	2007	DEA	-	-	-	-	✓
	Hong et al.	2005	MP(MIP)	-	-	-	-	✓
	Karpak et al.	2001	GP	-	-	-	-	✓
	Akarte et al.	2001	AHP	-	-	-	-	✓
	Muralidharan et al.	2002	AHP	-	-	-	-	✓
	Hou & Su	2007	AHP & DSS	-	-	-	-	✓
	Levary et al.	2008	AHP	-	✓	-	-	✓
	Sarkis & Talluri	2002	ANP	-	-	-	-	✓
	Chen et al.	2020	Six Sigma Quality Index Qpk	-	-	-	-	✓
	Pitchipoo et al.	2012	AHP-GRA	-	-	-	-	✓
	Kull & Talluri	2008	AHP & GP	-	✓	-	-	✓
	Shemshadi et al.	2011	Fuzzy TOPSIS & ANP	-	✓	-	-	✓
	Jain et al.	2018	Fuzzy AHP & TOPSIS	-	-	-	-	✓
	You et al.	2015	ITL-VIKOR	-	-	-	-	✓

Table 1. A Review of Relevant Literature

Approach	Author	Year	Research Methods	Group Suppliers	Risk Criteria	Cluster Analysis	DBCM*	Case Study
	Ha & Krishnan	2008	AHP & DEA & NN	-	-	✓	-	✓
	Rezaei & Ortt	2013	Fuzzy AHP	✓	-	-	-	✓
	Rezaei et al.	2015	BWM	-	-	-	-	✓
	Chen & Wu	2013	MFMEA & AHP	-	✓	-	-	✓
	Mavi et al.	2016	Shannon entropy & Fuzzy TOPSIS	-	✓	-	-	-
	Parkouhi et al.	2019	GDEMATEL & GSAW	✓	-	-	-	✓
	Luan et al.	2019	GA & ACO	✓	-	✓	-	-
	Maghsoodi et al.	2018	CLUS-MCDA	✓	-	✓	-	✓
	Zhang et al.	2006	K-Means	✓	-	✓	-	✓

* Density-Based Clustering Method

Rao et al. (2017) attempted to identify supplier selection criteria using the literature and identified 11 criteria, including four business criteria and seven supply chain risk criteria. Mavi et al. (2016) recognized nine criteria for supplier selection according to the opinions of seven supply chain experts with at least ten years of experience. Their criteria included quality, delivery time, past performance, supply risk, demand risk, logistics risk, information risk, and environmental risk. Torres-Ruiz and Ravindran (2018) identified vulnerability (risk) criteria at the supplier level and divided them into two main groups, namely, risks related to business performance, and environmental/social risks. Song et al. (2017) identified 20 risk factors of a sustainable supply chain and categorized them into four groups, including operational risks, economic risks, environmental risks, and social risks. Climate change and land-use dynamics can intensify environmental stress across geographical regions (Heidari et al., 2025).

Supplier Evaluation and Selection

A supplier selection problem is a multi-criteria problem, including some qualitative and quantitative factors mentioned in several studies. Various methods, such as multi-criteria decision-making techniques, data envelopment analysis (DEA), linear programming, neural networks, fuzzy approaches, etc., have been proposed for supplier selection under uncertainty and risk (Azadeh & Alem, 2010; Boran et al., 2009; Vanany et al., 2009). Wetzstein et al. (2019) reviewed 246 papers related to supplier selection problem over the years 1991-2017. They classified six knowledge references, including the conceptual base of the concept, purchase environment modeling, group decision-making and default input data, computational research, green research/sustainability, and risk-based supplier selection (Wetzstein et al., 2019). A supplier selection method should be applied in real conditions to provide desirable results and can improve the company status. Researchers have proposed various methods for

supplier selection (Khaleie et al., 2012). In recent years, researchers have focused on mathematical methods to resolve the supplier evaluation and selection problem (Agarwal et al., 2011). Employing a review of 68 papers over the years 2000-2011, multi-criteria decision-making methods were recognized as the most frequently used method for dealing with the supplier evaluation and selection problem. According to their results, DEA (30%), mathematical programming models (17%), analytical hierarchy process (15%), evidential reasoning (11%), fuzzy sets theory (10%), miscellaneous multi-criteria decision-making methods such as ELLECTRE and PROMETTE (7%), analytic network process (5%), multi-characteristic simple ranking II (3%), and genetic algorithm (2%) were the most frequently used approaches, respectively. Table 2 compare the relevant research.

Table 2. A Review and Comparison of Studies on Supplier Evaluation and Selection

Author	Year	Research Methods	Group Suppliers	Risk Criteria	Cluster Analysis	DBCM	Case Study
Tricaud & Chen	2010	K-Means & SA & PSO & Taguchi	-	-	✓	-	✓
Şahin & Supçiller	2015	AHP & TOPSIS & K-MEANS	✓	-	✓	-	✓
Vickers	2012	K-Means & SA & Taguchi- AHP	-	-	✓	-	✓
Bottani & Rizzi	2008	CA & MCDM & Fuzzy logic	✓	-	✓	-	✓
Azadnia et al.	2011	Fuzzy C-Means & Fuzzy AHP & ELECTERE	✓	-	✓	-	✓
Khaleie et al.	2012	IFC	-	-	✓	-	✓
Haghighi et al.	2014	AHP & LinPreRa -Fuzzy C-Means	✓	-	✓	-	✓
Heidarzade et al.	2016	IT2FS	-	-	✓	-	✓
Er Kara & Firat	2018	BWM & K-MEANS	✓	✓	✓	-	✓
Keskin et al.	2010	FuzzyART	✓	-	✓	-	✓
Akman	2015	Fuzzy C-Means & VIKOR	✓	-	✓	-	✓
Bottani et al.	2018	QFD-ANP	-	✓	-	-	✓
Current Study	2021	BWM & DBSCAN	✓	✓	✓	✓	✓

The comparative analysis presented in Table 3 clearly highlights the positioning of the proposed study within the existing literature. While several studies have addressed supplier selection using multi-criteria decision-making methods and clustering techniques, most of them rely on traditional clustering algorithms such as K-means or fuzzy clustering, which require predefined cluster numbers and do not effectively handle noise or irregular data structures.

In contrast, the proposed approach integrates the Best-Worst Method (BWM) for criteria weighting with the DBSCAN density-based clustering algorithm, enabling both robust handling of multi-criteria risk evaluation and automatic identification of supplier clusters

without requiring a predefined number of clusters. Moreover, the ability of DBSCAN to detect noise suppliers provides an additional advantage in real-world industrial environments with heterogeneous supplier data.

Supplier Evaluation and Selection Risk Criteria

According to the literature, quality, innovation, and research and development (R&D), flexibility, delivery performance, supplier specification and past performance, price level, financial stability, delivery time, supplier's capacity constraint, supplier's financial and economic status, responsibility and issue solving, managerial performance, geographical concentration, and information are, respectively, identified as some of the most important criteria. Then, packaging and transportation quality and logistics, supplier's production system and machinery, guarantee policy and after-sale services, quality commitment, accessibility and communication, supplier's ethical conditions, the strategic power of business, reliability, supplier's price and payment policy, dependence on contract relationships and outsourcing, and cultural propriety, respectively, have the highest importance among other criteria. Table 3 present the literature related to risks identified.

Table 3. Identified Risks Related to Suppliers

Number	Risk Criteria	Risk Sources
1	Quality of raw material	Alikhani et al. (2019); Er Kara & Fırat (2018); Mavi et al. (2016); Micheli et al. (2009); Rao et al. (2017); Ravindran et al. (2010); Schoenherr et al. (2008); Torres-Ruiz & Ravindran (2018); Xiao et al. (2012); Zouggari & Benyoucef (2012)
2	Supplier flexibility	Er Kara & Fırat (2018); Hamdi et al. (2018); Ho et al. (2010); Micheli et al. (2009); Ravindran et al. (2010); Song et al. (2017)
3	Delivery performance	Fathi et al. (2025); Schoenherr et al. (2008); Torres-Ruiz & Ravindran (2018); Xiao et al. (2012); Zouggari & Benyoucef (2012)
4	Ability to meet demand volume (production capacity)	Fathi et al. (2025); Micheli et al. (2009); Rao et al. (2017), Xiao et al. (2012)
5	Financial stability	Alikhani et al. (2019); Hallikas et al. (2004); Häntsch & Huchzermeier (2013); Micheli et al. (2009); Rao et al. (2017); Song et al. (2017); Torres-Ruiz & Ravindran (2018)
6	Delivery time	Alikhani et al. (2019); Er Kara & Fırat (2018); Mavi et al. (2016); Micheli et al. (2009); Rao et al. (2017); Ravindran et al. (2010); Schoenherr et al. (2008)
7	Technology and research and development	Ellram (1990); Er Kara & Fırat (2018); Micheli et al. (2009); Rao et al. (2017); Ravindran et al. (2010); Schoenherr et al. (2008); Song et al. (2017); Xiao et al. (2012); Zouggari & Benyoucef (2012)
8	Price policy and supplier payment	Micheli et al. (2009); Torres-Ruiz & Ravindran (2018)
9	Quality of transportation, packaging and logistics	Er Kara & Fırat (2018); Mavi et al. (2016); Micheli et al. (2009); Schoenherr et al. (2008)
10	Product price level	Alikhani et al. (2019); Er Kara & Fırat (2018); Rao et al. (2017); Ravindran et al. (2010); Torres-Ruiz & Ravindran (2018); Zouggari & Benyoucef (2012)
11	Financial and economic status	Alikhani et al. (2019); Er Kara & Fırat (2018); Hallikas et al. (2004); Micheli et al. (2009); Xiao et al. (2012)
12	Supplier specifications and past performance	Alikhani et al. (2019); Er Kara & Fırat (2018); Goh et al. (2007); Hallikas et al. (2004); Mavi et al. (2016); Song et al. (2017); Xiao et al. (2012); Zouggari & Benyoucef (2012)
13	Warranty and after-sales service	Er Kara & Fırat (2018); Mavi et al. (2016); Torres-Ruiz & Ravindran (2018)

Table 3. Identified Risks Related to Suppliers

Number	Risk Criteria	Risk Sources
14	Information	Alikhani et al. (2019); Mavi et al. (2016); Micheli et al. (2009); Rao et al. (2017); Song et al. (2017)
15	Managerial performance	Micheli et al. (2009); Rao et al. (2017); Schoenherr et al. (2008); Torres-Ruiz & Ravindran (2018); Xiao et al. (2012)
16	Supplier ethical conditions	Alikhani et al. (2019); Rao et al. (2017); Song et al. (2017)
17	Dependence on contractual relations and outsourcing	Er Kara & Fırat (2018)
18	Commitment to quality	Er Kara & Fırat (2018); Torres-Ruiz & Ravindran (2018); Xiao et al. (2012)
19	Access and communication	Er Kara & Fırat (2018); Ravindran et al. (2010); Xiao et al. (2012)
20	Reliability	Alikhani et al. (2019); Er Kara & Fırat (2018)
21	Responsibility and issue solving	Er Kara & Fırat (2018); Hong et al. (2005); Ravindran et al. (2010); Song et al. (2017); Xiao et al. (2012); Zouggari & Benyoucef (2012)
22	Geographical location	Alikhani et al. (2019); Micheli et al. (2009); Rao et al. (2017); Schoenherr et al. (2008); Zouggari & Benyoucef (2012)
23	Supplier's production system and machinery	Alikhani et al. (2019); Er Kara & Fırat (2018); Xiao et al. (2012)
24	Cultural propriety	Ellram (1990)
25	Strategic power of business	Hallikas et al. (2004); Ravindran et al. (2010) Torres-Ruiz & Ravindran (2018)

Research Framework

Regarding the research title, the present research addresses the selection of a group of suppliers based on their risk using the DBSCAN method. For this purpose, regarding the importance of the problem and the necessity for considering a sufficiently large company, a part manufacturing company was selected, which is the largest manufacturer of powertrains in the Middle East.

Case study

A part manufacturing company, known as the largest manufacturer of powertrains in the Middle East, was considered for the case study. This company is known as the main manufacturer of powertrains in Iran due to technological capabilities, high design power, the use of new technologies, and organizational excellence. The most important tasks of the company are manufacturing powertrains, supply chain management, and managing subsidiaries. This company was tasked with reducing the dependence of the domestic car industry on foreign companies in the area of powertrains production. In this model, the company's supplier network is divided into some levels, including main suppliers, first-level, second-level, and third-level suppliers. Some relevant roles are specified according to the level of each supplier and how it relates to the company. Figure 1 presents this relationship. In this research, 70 large suppliers were considered, including 67 domestic suppliers and three foreign suppliers.

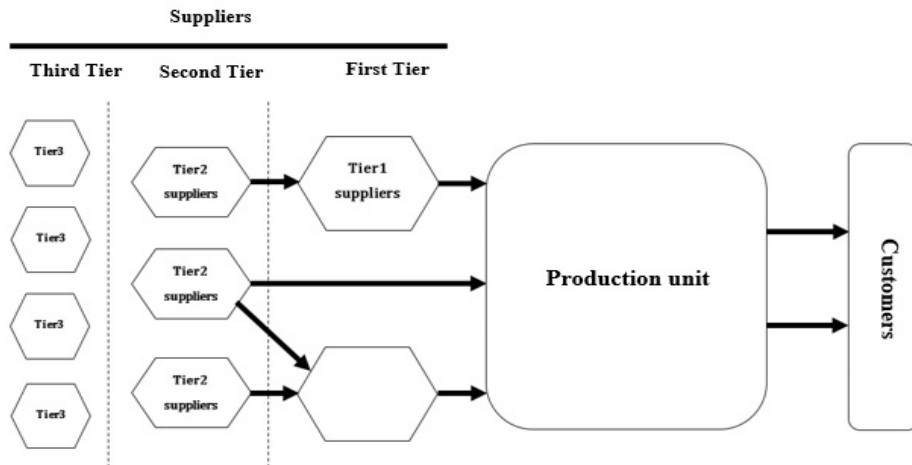


Figure 1. Supplier Network

Car manufacturing is one of the main parts of trade and industry in the world, and its supply chain is considered one of the most dynamic supply chains in the industrial sector. Final products of car manufacturers are emerged by an astute plan and integration at the level of a powerful supply chain. Therefore, an occurrence of risk in each segment of the chain, particularly the supply of raw materials and components, leads to a disruption in the whole of the chain. Accordingly, selecting some suppliers by considering the risks of the supply chain can be a fundamental action to prevent and control risk factors.

The Proposed Multi-Stage Model

In the first step, we seek to review relevant resources to collect comprehensive information on techniques used in the area of supplier selection. Then, the criteria are summarized, and their weights are derived using the BWM method. Finally, suppliers are clustered using the DBSCAN method. The model and its flowchart are presented in Figure 2.

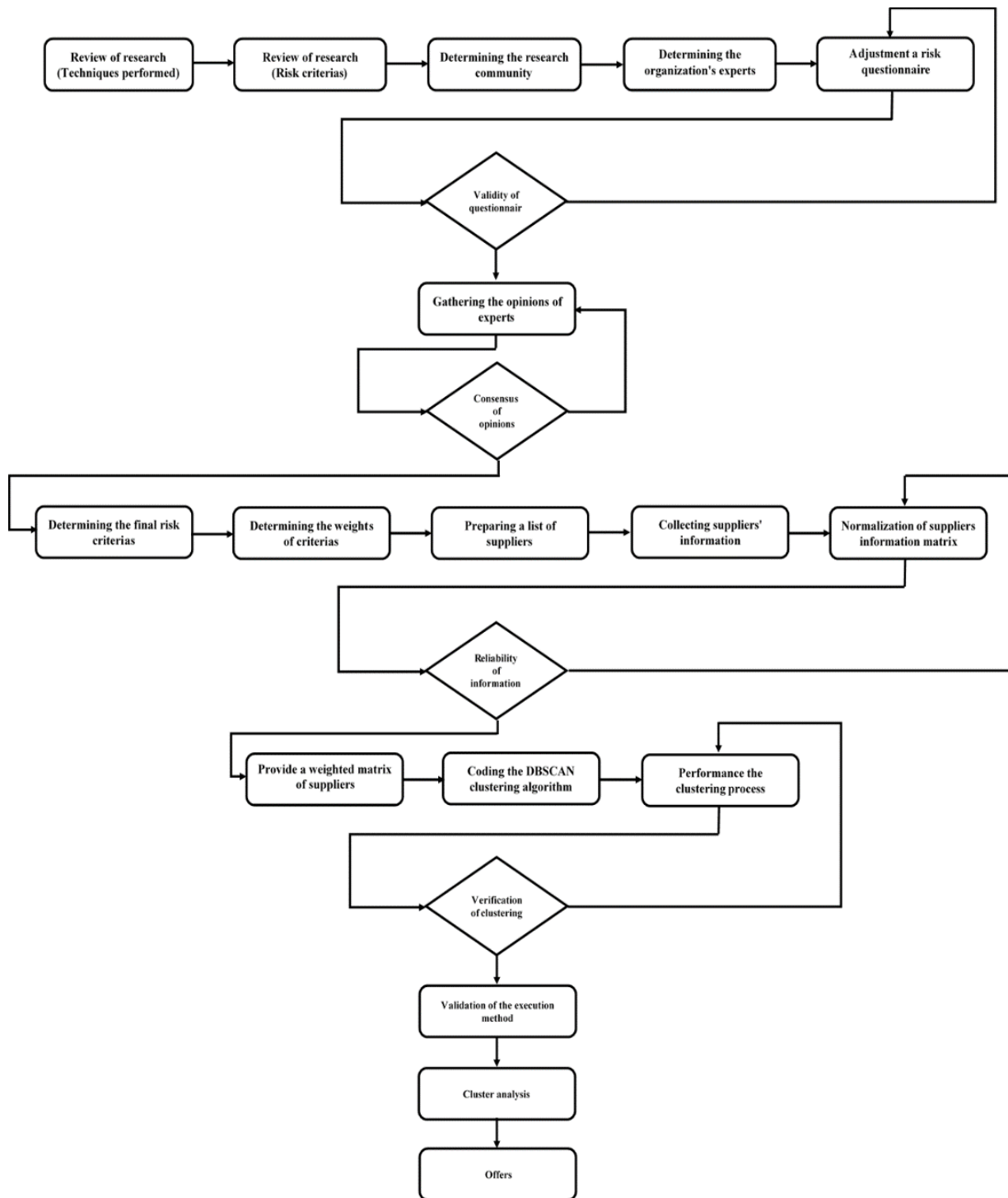


Figure 2. The Proposed Multi-Stage Model Structure

Research findings based on the conceptual model

The risk criteria identified were introduced in Section 3. Then, the final criteria were identified using 11 experts from the organization in a three-stage fuzzy Delphi process. The experts were among the senior specialists in planning, supply, and quality assurance unit of the organization. Finally, 24 risk criteria were specified by checking the reliability of the questionnaire in each step and using the experts' opinions. Table 3 shows the final risk criteria.

Table 4. Final Risk Criteria

Row	Risk Criterion	Row	Risk Criterion
1	The quality of raw material	13	Guarantee policy and aftersales services
2	Supplier's flexibility	14	Information
3	Delivery performance	15	Managerial performance
4	The capability to meet the demand (production capacity)	16	Supplier's ethical conditions
5	Financial stability	17	Dependence on contract relationships and outsourcing
6	Delivery time	18	Quality commitment
7	Technology, and research and development (R&D)	19	Accessibility and communication
8	Supplier's price and payment policy	20	Reliability
9	Packaging and transportation, quality and logistics	21	Responsiveness and issue solving performance
10	Price level	22	Geographical concentration
11	Financial and economic state	23	Production system and machinery
12	Supplier's specifications and past performance	24	Cultural propriety

Evaluating the Risk Criteria

After the final criteria were specified, the BWM method (Rezaei, 2015) was used to determine the weights of criteria. Among the final criteria, three, namely, the quality of raw materials, delivery performance, and delivery time, are quantitative, while the rest are qualitative. In this method, first, the best (most important) and the worst (least important) criteria are chosen, and the priority of the worst and best criteria related to other criteria is assessed. The four decision-makers under consideration are among the senior managers of the quality and supply assurance unit. Using a nine-point scale, decision-makers determine the priority of the best criterion over the other criteria as well as the priority of the other criteria over the worst criterion. Table 5 shows the scale used for pairwise comparisons.

Table 5. The Scale Used for Pairwise Comparisons of Criteria

Definition	Description	Point
Equal importance	If criterion A has equal importance, compared with criterion B	1
Low importance	If criterion A is slightly prioritized than criterion B	3
High importance	If criterion A is more prioritized than criterion B	5
Very high importance	If criterion A is highly prioritized than criterion B	7
The complete and absolute importance	If criterion A is absolutely prioritized than criterion B	9
Intermediate values	If there is an intermediate state (For example, an eight indicates higher importance than seven and lower importance than nine)	2-4-6-8

In the BWM procedure, decision-makers first expressed their preferences using qualitative judgments regarding the relative importance between criteria. These qualitative assessments were subsequently converted into numerical values according to the nine-point preference scale shown in Table 6. More specifically, values closer to one indicate equal importance, whereas larger values indicate stronger preference or greater dominance of one criterion over another. These numerical judgments were then used to construct the Best-to-Others and Others-to-Worst comparison vectors required for implementing the BWM methodology. Therefore, the values presented in Table 8 represent the numerical transformation of experts' qualitative assessments based on the adopted preference scale. Experts' opinions on the best and worst criteria are represented in Table 6.

Table 6. The Best and Worst Criteria Identified by Four Decision-Makers

Decision-Makers	The Best Criteria	The Worst Criteria
First decision-maker	Managerial performance (15)	Cultural propriety (24)
Second decision-maker	Quality commitment (18)	Cultural propriety (24)
Third decision-maker	Reliability (20)	Information (14)
Forth decision-maker	Production system and machinery (23)	Geographical location (22)

After specifying the best and worst criteria according to decision-makers' views, a pairwise comparison with the best and worst criteria, as illustrated in Table 7, was accomplished. Table 8 represents the results.

Table 7. A comparison of the Best and Worst Criteria with Other Criteria

	First DM		Second DM		Third DM		Forth DM	
	Best Criteria (15)	Worst Criteria (24)	Best Criteria (18)	Worst Criteria (24)	Best Criteria (20)	Worst Criteria (14)	Best Criteria (23)	Worst Criteria (22)
1	3	6	2	9	3	6	2	8
2	1	7	5	5	2	8	7	5
3	2	7	5	5	2	8	7	5
4	3	6	5	5	2	7	5	4
5	5	5	7	4	4	6	9	3
6	3	6	7	4	4	7	9	3
7	7	4	2	8	6	5	1	7
8	5	5	6	5	4	6	5	3
9	7	6	3	7	6	5	2	5
10	3	7	7	5	3	6	7	3
11	3	7	7	5	4	6	7	3
12	1	4	3	6	2	7	3	7
13	7	4	2	7	6	5	2	7
14	8	2	8	3	8	1	9	2
15	1	8	6	4	2	8	7	3
16	7	2	4	3	8	5	9	1
17	8	3	8	5	7	6	9	2
18	5	4	1	9	5	5	1	8
19	7	3	3	5	7	4	6	3
20	2	7	5	6	3	7	5	5
21	6	5	3	6	5	5	2	7
22	3	3	9	3	4	3	9	1

Table 7. A comparison of the Best and Worst Criteria with Other Criteria

	First DM		Second DM		Third DM		Forth DM	
	Best Criteria (15)	Worst Criteria (24)	Best Criteria (18)	Worst Criteria (24)	Best Criteria (20)	Worst Criteria (14)	Best Criteria (23)	Worst Criteria (22)
23	5	5	2	8	5	6	1	8
24	8	1	9	1	8	2	9	2

The optimal weights for each decision-maker were obtained based on the data in Table 8 and by solving the Equation (1) using the GAMS software. The values of the objective function for each supplier are as follows:

$$\begin{aligned}
 & \text{MIN } \xi \\
 & \text{s.t.} \\
 & |w_b - a_{Bj} w_j| \leq \xi \quad \text{for all } j \\
 & |w_j - a_{jw} w_w| \leq \xi \quad \text{for all } j \\
 & \sum_j w_j = 1 \\
 & w_j \geq 0, \text{ for all } j \\
 & \varepsilon_1 = 0.0354 \\
 & \varepsilon_2 = 0.03132 \\
 & \varepsilon_3 = 0.0383 \\
 & \varepsilon_4 = 0.03134
 \end{aligned} \tag{1}$$

All the values obtained for the objective function are close to zero. Thus, the comparisons of the four decision-makers can be accepted without a contradiction.

Before aggregating the weights obtained from the four decision-makers, the level of agreement among them was examined to ensure the reliability of the collective judgments. For this purpose, Kendall's coefficient of concordance (W) was employed to measure the degree of consensus among decision-makers regarding the pairwise comparison results. The calculated coefficient indicated an acceptable level of agreement among decision-makers, suggesting that their judgments were sufficiently consistent for aggregation. Therefore, the final weights of criteria were obtained using the arithmetic average of the individual BWM weights derived from the four decision-makers.

The final weights of the criteria were obtained by the averages of the weights obtained by four BWM problems. The optimal average values for 24 risk criteria are presented in Table 8. These weights will be used in subsequent sections to analyze the information.

Table 8. The Averages of the Weights Obtained by Four BWM Problems

	Values				
	DM1	DM2	DM3	DM4	
W1	0479.0	0.0767	0.0511	0.0731	0.0622
W2	1008.0	0.0307	0.0767	0.0208	0.0573
W3	0.0718	0.0307	0.0767	0.0208	0.0500
W4	0.0479	0.0307	0.0767	0.0292	0.0461
W5	0.0287	0.0219	0.0383	0.0162	0.0263

Table 8. The Averages of the Weights Obtained by Four BWM Problems

	Values				
	DM1	DM2	DM3	DM4	
W6	0.0479	0.0219	0.0383	0.0162	0.0311
W7	0.0205	0.0767	0.0255	0.1044	0.0568
W8	0.0287	0.0255	0.0383	0.0292	0.0304
W9	0.0205	0.0511	0.0255	0.0731	0.0426
W10	0.0479	0.0219	0.0511	0.0208	0.0354
W11	0.0479	0.0219	0.0383	0.0208	0.0322
W12	0.0728	0.0511	0.0767	0.0487	0.0623
W13	0.0205	0.0767	0.0255	0.0731	0.0490
W14	0.0179	0.0191	0.0191	0.0162	0.0181
W15	0.1082	0.0255	0.0767	0.0208	0.0578
W16	0.0205	0.0383	0.0191	0.0162	0.0235
W17	0.0179	0.0191	0.0219	0.0162	0.0188
W18	0.0287	0.1222	0.0307	0.1149	0.0741
W19	0.0205	0.0511	0.0219	0.0243	0.0295
W20	0.0718	0.0307	0.0511	0.0292	0.0457
W21	0.0239	0.0511	0.0307	0.0731	0.0447
W22	0.0479	0.017	0.0383	0.0104	0.0284
W23	0.0287	0.0767	0.0307	0.1149	0.0628
W24	0.0093	0.0101	0.0191	0.0162	0.0137

Clustering of Suppliers

Clustering is one of the most important problems in unsupervised learning whose objective is to find a meaningful structure within a data set. Indeed, clustering aims to divide an unlabeled set into similar groups such that data points in each group have the most similarity among them and the least similarity to other clusters. The DBSCAN algorithm clusters data according to density. In this approach, each data point is included in a cluster based on the number of data points in its neighborhood. The two parameters, i.e., ε and *Minpts*, play an important role in forming the clusters, and these parameters should be adjusted based on the type of data and problem.

Some advantages and important features of the DBSCAN algorithm, compared with other non-density-based algorithms, can be mentioned as follows:

- The capability for discovering clusters with arbitrary shapes
- The ability to diagnose noise points
- Being free of the need for specifying the number of clusters (This algorithm is categorized into the class of unsupervised algorithms).

Since the performance of DBSCAN strongly depends on the selection of ε and *MinPts* parameters, a systematic parameter tuning procedure was adopted. Different combinations of ε and *MinPts* values were examined through sensitivity analysis, and the resulting clustering structures were evaluated using several performance indicators, including inter-cluster distance, intra-cluster distance, the number of clusters formed, and the number of identified noise points. The purpose of this process was to identify parameter combinations capable of generating meaningful and well-separated clusters while maintaining adequate cluster compactness. Based on this analysis, the parameter values ($\varepsilon = 0.00055$, *MinPts* = 2) were selected because they

produced the most appropriate trade-off between cluster separation, cluster compactness, and interpretability of results.

Generally, the company under study deals with some small, medium, and large suppliers. Totally, 70 engine manufacturers, which are the key suppliers for this company, were considered consisting of 67 domestic suppliers and three foreign suppliers. The suppliers were analyzed based on the information given by the organization's decision-makers regarding the 24 risk criteria described in previous sections. Since the output values of suppliers' information have been assessed based on the risk criteria using different scales, a normalization process is required to normalize the data. Therefore, data can be prepared using the following normalization equation:

$$\frac{x_{ij}}{\sum_{i=1}^m x_{ij}} \quad (2)$$

After the data normalization, the weights of the risk criteria, presented in Table 7, are incorporated in the normalized matrix, and the final matrix with the dimensions 70×24 is obtained as the input for clustering.

Results of the Proposed Approach

The clustering algorithm was coded and implemented by the MATLAB R2018b software. The input parameters, including the weighted matrix of suppliers (X) with dimensions 70×24 , the neighborhood radius (ε), and the minimum number of points in a neighborhood of the center point ($Minpts$), were specified and entered into the algorithm. The results of clustering based on 24 risk criteria were also obtained by the IDX variable. The results are represented in Table 10. Figure 3 presents the graphical representation of clustering results obtained from the DBSCAN algorithm. To improve interpretability, suppliers are visualized using reduced-dimensional coordinates, where different groups indicate cluster memberships and isolated observations represent noise points detected by the algorithm. Axis labels and cluster indicators are provided to facilitate the interpretation of clustering patterns and supplier distribution.

As observed, four clusters are obtained using the DBSCAN algorithm with parameters $\varepsilon = 0.00055$, and $Minpts = 2$. The values of inter- and intra-cluster distance resulted from the algorithm are at the most optimal state (Inter = 0.001 and Intra = 0.00017387), indicating the consistency of clustering results.

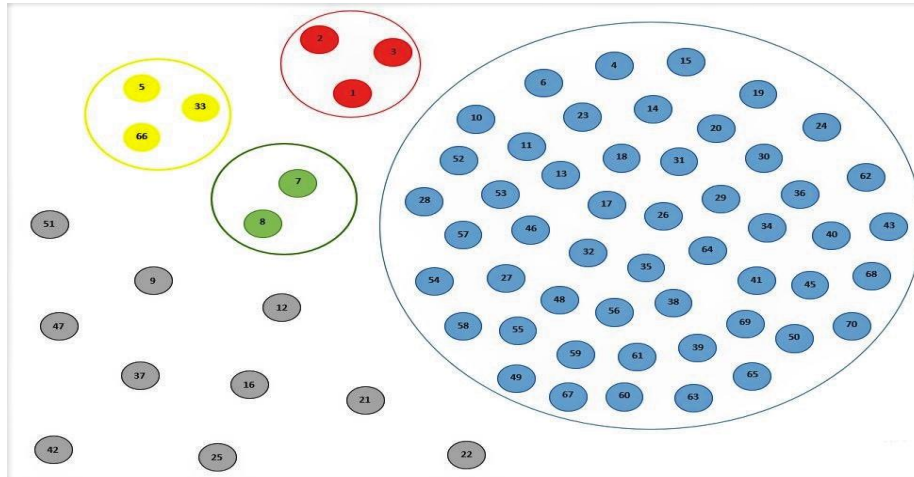


Figure 3. A Symbolic Graph of Supplier Clustering Using the DBSCAN Algorithm

Table 9. Supplier Clustering Based on Risk Criteria

Noise Points	Points of Cluster	Number of Noise	Cluster	Output Parameters	Input Parameters
	S_1, S_2, S_3	3	Cluster 1		
	$S_4, S_6, S_{10}, S_{11}, S_{13}, S_{14}, S_{15}, S_{17}, S_{18}, S_{19}, S_{20}, S_{23}, S_{24}, S_{26}, S_{27}, S_{28}, S_{29}, S_{30}, S_{31}, S_{32}, S_{34}, S_{35}, S_{36}, S_{38}, S_{39}, S_{40}, S_{41}, S_{43}, S_{45}, S_{46}, S_{48}, S_{49}, S_{50}, S_{52}, S_{53}, S_{54}, S_{55}, S_{56}, S_{57}, S_{58}, S_{59}, S_{60}, S_{61}, S_{62}, S_{63}, S_{64}, S_{65}, S_{67}, S_{68}, S_{69}, S_{70}$	51	Cluster 2		
	S_5, S_{33}, S_{66}	3	Cluster 3		
	S_7, S_8	2	Cluster 4		

As previously mentioned, one of the advantages of the DBSCAN algorithm against other clustering algorithms is its ability to diagnose noise points. As seen in Table 10, clusters 1 to 4 consist of 3, 51, 3, and 2 supplier nodes, respectively. According to the clustering results, the points $S_9, S_{12}, S_{16}, S_{21}, S_{22}, S_{25}, S_{37}, S_{42}, S_{47}, S_{51}$ constitute the noise points, respectively.

These suppliers were identified as noise points, as they failed to satisfy the density requirements defined by the selected DBSCAN parameters. More specifically, these observations did not contain a sufficient number of neighboring suppliers within the specified ϵ -neighborhood and therefore could not be assigned to any existing cluster. The identified noise suppliers exhibited relatively heterogeneous risk profiles and lower similarity with surrounding observations across the evaluated risk criteria. Consequently, their classification as noise indicated isolated or atypical supplier behavior rather than merely reflecting high-risk characteristics. The clustering results are assessed using inter- and intra-cluster distances.

- **Inter-cluster distance:** It is defined as the distance between a point in a cluster and the center of the same cluster given by equation (3). In this equation, n denotes the number of objects within the data set.

$$Intra = \frac{1}{n} \sum_{i=1}^k \sum_{x_j \in c_i} \|x_j - z_i\|^2 \quad (3)$$

- Intra-cluster distance: It is defined as the distance between the centers of clusters and obtained by the following equation.

$$Inter = \frac{1}{k} \sum \|z_i - z_j\|^2, i = 1, 2, \dots, k-1, j = i+1, i+2, \dots, k \quad (4)$$

Analysis of Results

Clustering validity

After the implementation of clustering on a data set, the quality of results should be assessed. A clustering approach should produce clusters in which the inter-cluster similarity is minimized, while the intra-cluster similarity is maximized. In other words, inter-cluster distances are minimized, and intra-cluster distances are maximized. For this purpose, inter- and intra-cluster distances are used to examine and validate input parameters and assess the output. Some results are presented in Table 10 for comparison and evaluation.

Table 10. Analysis of Input Parameters

Input Parameters		Number of Clusters	Number of Noise	Intra-Cluster Distance (Intra)	Inter-Cluster Distance (Inter)
$\varepsilon = 0.0002$	Minpts = 2	1	68	6.7573E-05	0
$\varepsilon = 0.00025$	Minpts = 2	4	62	1.0620E-04	7.4764E-04
	Minpts = 2	6	57	1.1185E-04	7.3614E-04
	Minpts = 3	1	67	9.4536E-05	0
	Minpts = 3	1	67	9.4536E-05	0
$\varepsilon = 0.00035$	Minpts = 2	8	53	1.2278E-04	7.2637E-04
	Minpts = 2	10	40	1.6062E-04	7.9257E-04
	Minpts = 3	4	52	1.2329E-04	6.2773E-04
	Minpts = 4	2	61	9.6992E-05	3.4846E-04
	Minpts = 2	5	26	1.6530E-04	8.1347E-04
	Minpts = 3	2	32	1.5225E-04	5.0054E-04
	Minpts = 4	2	38	1.6715E-04	5.9122E-04
	Minpts = 6	2	56	1.0486E-04	2.5099E-04
	Minpts = 2	8	22	1.7596E-04	8.3195E-04
	Minpts = 2	6	21	1.7540E-04	8.3195E-04
$\varepsilon = 0.00048$	Minpts = 2	5	20	1.5901E-04	8.1347E-04
	Minpts = 4	2	28	1.3932E-04	5.0054E-04
	Minpts = 2	5	15	1.6641E-04	9.7980E-04
	Minpts = 3	3	19	1.5052E-04	6.4379E-04
	Minpts = 2	5	15	1.6641E-04	9.7980E-04
	Minpts = 3	3	19	1.5052E-04	6.4379E-04
	Minpts = 4	2	22	1.3204E-04	5.0054E-04
	Minpts = 2	4	10	1.7387E-04	0.001
	Minpts = 3	3	13	1.6555E-04	9.1885E-04
	Minpts = 4	2	20	1.3154E-04	5.0054E-04
	Minpts = 5	2	21	1.2600E-04	5.0054E-04
	Minpts = 2	3	10	1.9341E-04	9.5108E-04

Input Parameters		Number of Clusters	Number of Noise	Intra-Cluster Distance (Intra)	Inter-Cluster Distance (Inter)
$\varepsilon = 0.00057$	Minpts = 3	3	10	1.6270E-04	9.5384E-04
	Minpts = 4	2	18	1.3988E-04	5.0054E-04
$\varepsilon = 0.0006$	Minpts = 2	1	9	1.1713E-04	0

The selection of the final parameter configuration was not based exclusively on a single performance metric. Although the parameter combination ($\varepsilon = 0.00055$, MinPts = 3) produced slightly lower intra-cluster distance, the configuration ($\varepsilon = 0.00055$, MinPts = 2) provided larger inter-cluster separation while simultaneously generating clustering structures with higher interpretability and more meaningful supplier categorization. Therefore, the final parameter selection was determined based on achieving a balanced trade-off among cluster compactness, cluster separation, the interpretability of clustering structure, and the capability of identifying meaningful noise observations.

Model Validation

Despite its advantages against other non-density-based algorithms, the DBSCAN algorithm has not been still used in the area of supplier clustering. This method is based on unsupervised clustering since the number of clusters is not previously specified, and there is no label exhibiting a prior partitioning of data.

Inter- and intra-cluster distances were calculated by considering different parameters to assess the validity of the clustering results. Now, the data are clustered using the unsupervised K-means approach by the SPSS 25 software to assess the validity of the results. For this purpose, the number of clusters is considered to be four, and the inter- and intra-cluster distances are compared.

Cluster centers obtained by K-means clustering are presented in Table 11. The average distance between the points and the cluster center and average distance between the centers of clusters are used to derive inter- and intra-cluster distances, respectively. The results are Intra = 0.000444 and Inter = 0.000935.

Table 11. Cluster Centers in K-Means Clustering

	Centers of Clusters			
	Cluster 1	Cluster 2	Cluster 3	Cluster 4
C1	0.001923474	0.000584132	0.001139569	0.000749457
C2	0.000825225	0.000788924	0.000957851	0.000861745
C3	0.000795544	0.000577184	0.00020781	0.000881724
C4	0.000694211	0.000674023	0.000734262	0.000621075
C5	0.000416727	0.000344545	0.000494422	0.000416113
C6	0.000705182	0.000254553	0.000141036	0.000682697
C7	0.000852035	0.000831253	0.00090119	0.000762272
C8	0.000453489	0.000425335	0.000494715	0.000444527
C9	0.000658367	0.000579862	0.000792479	0.000638754
C10	0.000530892	0.000493224	0.000579155	0.0005204
C11	0.000496451	0.000427043	0.000576238	0.000506858
C12	0.000961488	0.00082497	0.000111601	0.000981643
C13	0.00070832	0.000674077	0.000822158	0.000736917

C14	0.00026116	0.00025032	0.000297814	0.000269925
C15	0.000889231	0.000775642	0.000979661	0.000894473
C16	0.000374849	0.000282161	0.000517033	0.000415874
C17	0.000231149	0.000273836	0.00021228	0.000268683
C18	0.001143366	0.000992587	0.001259641	0.001150107
C19	0.000426053	0.000407458	0.00048585	0.000440353
C20	0.000706094	0.000623493	0.000849928	0.000685059
C21	0.000780676	0.000572762	0.000818451	0.000717171
C22	0.000349648	0.000414217	0.000321106	0.000406423
C23	0.001095915	0.000804045	0.001148944	0.001006767
C24	0.000217898	0.000164019	0.000300549	0.000241746

The results of the K-means algorithm obtained using the same weighted normalized dataset are presented in Table 13. As seen, the unsupervised approach of DBSCAN with four clusters provides better results, compared with the other method.

To ensure a fair comparison between clustering approaches, both DBSCAN and K-means were implemented using the same input dataset and preprocessing procedure. More specifically, the weighted normalized decision matrix obtained from the supplier risk evaluation stage was used as the input for both algorithms. Therefore, differences observed in clustering performance are attributable to the clustering mechanisms themselves rather than differences in data preprocessing or normalization procedures.

Table 12. Model Validation

Distances	Clustering Based on DBSCAN	Clustering Based on K-means
Intra	0.00017387	0.000444
Inter	0.001025	0.000935

Cluster Analysis

This study aimed to cluster the suppliers of the Mega Motor Company based on various risk criteria. Totally, 70 engine suppliers for this company are assessed in terms of quantitative and qualitative data related to risk factors. The DBSCAN algorithm is generally used due to its capability to identify noise points, diagnose clusters with arbitrary shapes, and being used with large-scale data. This approach is used to find similarities between the suppliers based on different risk criteria.

Four clusters, consisting of 3, 51, 3, and 2 suppliers with different risk levels, were obtained. Table 14 shows the center of clusters. Red, yellow, orange, and green cells represent high, medium to high, low to medium, and low risk, respectively. As seen, cluster 3 is subject to the highest risk level for all risks, including the quality of raw material, production capacity, financial stability, managerial performance, reliability, etc. This cluster can be considered as a cluster of high-risk suppliers. Cluster 1 has the lowest risk in terms of managerial performance, quality commitment, responsiveness performance and issue solving, production system, machinery, etc. This cluster can also be called low-risk suppliers. The suppliers belonging to this cluster have the highest score in some criteria, including dependence on contract relationships or outsourcing, geographical location, the final price of the product, supplier's price and payment policy, and technology. Additionally, these suppliers have a low-to-medium

risk for the organization in terms of some criteria, including production capacity, transportation quality, and accessibility and reliability.

Table 13. The Average of 17 Risk Criteria Based on the Four Clusters

Risk Factor	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Quality of raw material	0.000888	0.000605	0.001627	0.00015776
Supplier flexibility	0.000663	0.000821	0.000786	0.00077365
Delivery performance	0.000871	0.000599	0.000778	0.00112113
Ability to meet demand volume	0.000668	0.000677	0.000712	0.00060076
Financial stability	0.000224	0.000364	0.000412	0.00040613
Delivery time	0	0.000357	0.000737	0.00079921
Technology and research and development	0.000874	0.000831	0.000874	0.00073734
Price policy and supplier payment	0.000536	0.000422	0.000453	0.00041226
Quality of transportation, packaging and logistics	0.000508	0.000607	0.000671	0.00048768
Product price level	0.000563	0.000494	0.000531	0.00048263
Financial and economic status	0.000355	0.000450	0.000488	0.00046542
Supplier specifications and past performance	0.000687	0.000870	0.000944	0.00090139
Warranty and after-sales service	0.000548	0.000703	0.000675	0.00063243
Information	0.000251996	0.00025245	0.000251996	0.00022909
Managerial performance	0.000628	0.000816	0.000854	0.00075359
Supplier ethical conditions	0.000129	0.000327	0.000366	0.00029083
Dependence on contractual relations and outsourcing	0.000346	0.000267	0.000212	0.00023587
Commitment to quality	0.000743	0.001049	0.001098	0.00096895
Access and communication	0.000399	0.000412	0.000411	0.00037373
Reliability	0.000567	0.000651	0.000719	0.00052303
Responsibility and problem solving	0.000420	0.000623	0.000818	0.00056662
Geographical location	0.000511	0.000405	0.000321	0.00035678
Supplier's production system and machinery	0.000589	0.000875	0.001149	0.00079542
Cultural propriety	0.000075	0.000190	0.000213	0.00016906

The suppliers belonging to the second cluster have a medium-to-high level of risk for many risk types. This cluster can be called the cluster of medium-to-high-risk suppliers. Finally, suppliers in the fourth cluster are called low-to-medium-risk suppliers. This cluster has the lowest level of risk in some criteria, including the quality of raw materials, production capacity, the price and payments policy, transportation quality, the final price of the product, accessibility, and reliability. According to the results, the company can cooperate with suppliers belonging to clusters with low-to-medium risk (clusters 1-2 and 4) and regard development plans for suppliers with a high level of risk (cluster 3). Furthermore, the company can act based on the weights obtained by its experts for the criteria and select the desired cluster. The noise points, i.e., suppliers belonging to none of the clusters, are not analyzable in any of the risk levels, reflecting their unpredictable behavior. Obviously, according to the results and information obtained by the DBSCAN approach about the noise points, these suppliers are overlooked in companies' decisions on purchase and the supply of materials and components.

Comparison between Proposed Model and Unsupervised Machine Learning

Machine learning techniques have recently achieved remarkable successes in analyzing large data sets in various areas. Machine learning techniques can be employed for various tasks

related to phase transitions, including the comparison of experimental data to competing theoretical descriptions in an unbiased way, the analysis of patterns in the trained filters of convolutional neural networks, the generation of new image, and the extraction of physical parameters and concepts. In this paper, we use the proposed method introduced by Kaming et al. (2021) to analyze the performance of the proposed model. The following table show the result of the comparison.

Table 14. Comparison between the Proposed Model with Kaming et al. (2021)

	Gap with the Best Cluster	
	Proposed Method	Kaming et al. (2021)
Quality of raw material	0.000158	0.001148
Supplier flexibility	0.000663	0.00178
Delivery performance	0.000599	0.001627
Ability to meet demand volume (production capacity)	0.000601	0.001493
Financial stability	0.000224	0.001302
Delivery time	0	0
Technology and research and development	0.000737	0.000166
Price policy and supplier payment	0.000412	0.0013
Quality of transportation, packaging and logistics	0.000488	0.001381
Product price level	0.000483	0.001388
Financial and economic status	0.000355	0.00151
Supplier specifications and past performance	0.000687	0.0001542
Warranty and after-sales service	0.000548	0.001399
Information	0.000229	0.001372
Managerial performance	0.000628	0.001677
Supplier ethical conditions	0.000129	0.001061
Dependence on contractual relations and outsourcing	0.000212	0.001267
Commitment to quality	0.000743	0.001581
Access and communication	0.000374	0.0001529
Reliability	0.000523	0.001667
Responsibility and problem solving	0.00042	0.001405
Geographical location	0.000321	0.001399
Supplier's production system and machinery	0.000589	0.001577
Cultural propriety	0.000075	0.001053

It should be noted that although the proposed DBSCAN-based approach demonstrates superior performance in most criteria, a slightly higher gap value is observed in the technology and research and development criterion compared to the method proposed by Kaming et al. (2021). This difference does not indicate a weakness of the proposed model, but rather reflects the fundamental distinction between density-based clustering and centroid-based approaches.

Specifically, DBSCAN forms clusters based on the overall density structure in a multidimensional weighted space, meaning that clustering quality is optimized at the global level across all risk dimensions simultaneously. As a result, local deviations in individual criteria may occasionally be higher when the global cluster structure is more stable and robust

against noise and heterogeneous observations. In contrast, methods such as the one proposed by Kaming et al. (2021) rely more on centroid-driven distance minimization, which can lead to improved performance in specific individual criteria such as technology and research and development; however, it may reduce global consistency and robustness of clustering structure.

Therefore, the observed difference in this specific criterion is attributed to the inherent trade-off between local feature-level accuracy and global clustering stability, which is a well-known characteristic in unsupervised clustering problems.

Conclusion

Appropriate supplier selection is crucial for the success of companies, and companies require long-term and strong relationships with suppliers to achieve their goals. The supply of raw materials and components contribute to a great share in the costs of a company, and supplier selection problem is an issue related to large companies. For this purpose, a part manufacturer, which is referred to as the largest producer of powertrains in the Middle East, is considered for the study. The problem is to select suppliers based on associated risk criteria using the DBSCAN approach. After the adjustment and final acceptance of 24 relevant criteria, their importance was assigned by the organization's decision-makers, and their weights were calculated by the BWM method. The weighted matrix was obtained by the matrix of criteria weights and information matrix of 70 identified suppliers based on risk criteria. In the final step, the DBSCAN approach was used to cluster the suppliers based on the related risks. This approach is used for supplier selection for the first time. The weights matrix, ε and $Minpts$, were used as input parameters. Four clusters, consisting of 3, 51, 3, and 2 suppliers, were obtained, and ten suppliers were identified as noise points. Inter- and intra-cluster distances under different values of ε and $Minpts$ were used to validate the clustering results, and their values (Intra = 0.000017387, and Inter = 0.001) meet the requirements. Since the approach used is a density-based, unsupervised method, which was applied here for the first time, the K-means clustering approach and the method proposed by Kaming et al. (2021), which are non-density-based supervised methods, were also used to validate the results (Er Kara & Firat, 2018). In contrast to DBSCAN, the K-means approach is a supervised approach requiring the number of clusters to be determined previously. Another weakness of this method is its inability to determine noise points. The SPSS 25 software was used, and four clusters were considered under the same conditions to compare the results. The values of inter- and intra-cluster distances with the K-means approach were obtained as 0.000444 and 0.000935, respectively. Therefore, the results of the DBSCAN method verify the model introduced. Cluster analysis was carried out using the average score for clusters in terms of 24 risk criteria. Cluster 1 was identified as the lowest-risk cluster based on the aggregated weighted evaluation of all 24 risk criteria. Although this cluster may exhibit higher values in some individual criteria compared to other clusters (e.g., the quality of raw material), the overall risk assessment is derived from the combined effect of all weighted criteria rather than isolated indicator comparisons. Therefore, the final cluster ranking reflects the holistic risk profile of suppliers, where Cluster 1 shows the most favorable (lowest-risk) overall condition, followed by Clusters 4, 2, and 3. The company is recommended to work with suppliers belonging to clusters 1, 2, and 4 based on its strategy and consider a development plan for suppliers in cluster 3. Furthermore, according to the

weights derived from the expert opinions in the area of quality and supply, some risk criteria, including quality commitment, production system and machinery, suppliers' specifications, prior performance, and the quality of raw materials have the highest importance, compared with other criteria. The Mega Motor Company can act based on the weight preference of the criteria mentioned. Accordingly, suppliers in cluster 1 have the lowest risk level based on the highly important criteria, including quality commitment, production system and machinery, and the supplier's specification. Moreover, suppliers belonging to cluster 3 have the highest level of risk based on the above criteria.

Future recommendations

The DBSCAN method is a density-based approach used for the first time for the supplier selection problem. Future studies are recommended to use non-density-based algorithms to cluster suppliers and compare the results. Furthermore, it is suggested to identify the most effective and affected factors using the DEMATEL and ANP methods and compare the clustering results using the factors identified. On the other hand, the fuzzy sets theory can be incorporated into the clustering process, and uncertainty can be considered in calculations.

Acknowledgements

The authors thank the Mega Motor Quality Assurance Unit and relevant experts for their valuable cooperation. Also, we thank the reviewers for their valuable and highly influential comments and recommendations.

Statements and Declarations

Ethics Statement: The author declares that this study was conducted in accordance with established ethical principles and guidelines. All sources of information have been properly cited and acknowledged. Where applicable, ethical approval was obtained, and informed consent was secured from all participants. The research did not involve any form of plagiarism, fabrication, or falsification of data.

Use of Artificial Intelligence: The author acknowledges that AI-based tools were used solely for language editing and grammar checking. All AI-assisted content was carefully reviewed, verified, and edited by the author, who takes full responsibility for the accuracy, originality, and integrity of the final manuscript. AI tools were not used to generate or manipulate research data or to replace critical scholarly judgment.

Originality and Publication: The author declares that this work has not been published previously and is not under consideration for publication elsewhere.

Conflicts of Interest: Any potential conflicts of interest, including financial or personal relationships that could influence the research, are disclosed. The author declares no competing interests.

Compliance with Regulations: The author confirms that the study complied with all applicable institutional, national, and international regulations, and that any necessary permissions for data use and reproduction have been obtained.

References

- Abdollahi, M., Arvan, M., & Razmi, J. (2015). An integrated approach for supplier portfolio selection: Lean or agile? *Expert Systems with Applications*, 42(1), 679–690. <https://doi.org/10.1016/j.eswa.2014.08.012>
- Agarwal, P., Sahai, M., Mishra, V., Bag, M., & Singh, V. (2011). A review of multi-criteria decision making techniques for supplier evaluation and selection. *International Journal of Industrial Engineering Computations*, 2(4), 801–810. <https://doi.org/10.5267/j.ijiec.2011.05.001>

- Akarte, M. M., Surendra, N. V., Ravi, B., & Rangaraj, N. (2001). Web-based casting supplier evaluation using analytical hierarchy process. *Journal of the Operational Research Society*, 52(5), 511–522. <https://doi.org/10.1057/palgrave.jors.2601129>
- Akman, G. (2015). Evaluating suppliers to include green supplier development programs via fuzzy c-means and VIKOR methods. *Computers & Industrial Engineering*, 86, 69–82. <https://doi.org/10.1016/j.cie.2015.03.015>
- Alikhani, R., Torabi, S. A., & Altay, N. (2019). Strategic supplier selection under sustainability and risk criteria. *International Journal of Production Economics*, 208, 69–82. <https://doi.org/10.1016/j.ijpe.2018.11.018>
- Arabsheybani, A., Paydar, M. M., & Safaei, A. S. (2018). An integrated fuzzy MOORA method and FMEA technique for sustainable supplier selection considering quantity discounts and supplier's risk. *Journal of Cleaner Production*, 190, 577–591. <https://doi.org/10.1016/j.jclepro.2018.04.167>
- Azadeh, A., & Alem, S. M. (2010). A flexible deterministic, stochastic and fuzzy data envelopment analysis approach for supply chain risk and vendor selection problem: Simulation analysis. *Expert Systems with Applications*, 37(12), 7438–7448. <https://doi.org/10.1016/j.eswa.2010.04.001>
- Azadnia, A. H., Saman, M. Z. M., Wong, K. Y., & Ghadimi, P. (2011). Supplier selection: A hybrid approach using ELECTRE and fuzzy clustering. In *International Conference on Informatics Engineering and Information Science* (pp. 214–224). Springer. https://doi.org/10.1007/978-3-642-25462-8_19
- Boran, F. E., Genç, S., Kurt, M., & Akay, D. (2009). A multi-criteria intuitionistic fuzzy group decision making for supplier selection with TOPSIS method. *Expert Systems with Applications*, 36(8), 11363–11368. <https://doi.org/10.1016/j.eswa.2009.03.039>
- Bottani, E., & Rizzi, A. (2008). An adapted multi-criteria approach to suppliers and products selection—An application oriented to lead-time reduction. *International Journal of Production Economics*, 111(2), 763–781. <https://doi.org/10.1016/j.ijpe.2007.03.012>
- Bottani, E., Centobelli, P., Murino, T., & Shekarian, E. (2018). A QFD-ANP method for supplier selection with benefits, opportunities, costs and risks considerations. *International Journal of Information Technology & Decision Making*, 17(3), 911–939. <https://doi.org/10.1142/S0219622018500206>
- Chan, F. T. S., & Kumar, N. (2007). Global supplier development considering risk factors using fuzzy extended AHP-based approach. *Omega*, 35(4), 417–431. <https://doi.org/10.1016/j.omega.2005.08.004>
- Chen, K. S., Huang, C. T., & Chang, T. C. (2020). Decision-making for the selection of suppliers based on the process quality assessment. *International Journal of Reliability, Quality and Safety Engineering*, 27(6), 2050016. <https://doi.org/10.1142/S021853932050016X>
- Chen, P.-S., & Wu, M.-T. (2013). A modified failure mode and effects analysis method for supplier selection problems in the supply chain risk environment: A case study. *Computers & Industrial Engineering*, 66(4), 634–642. <https://doi.org/10.1016/j.cie.2013.09.018>
- Chen, Y.-J. (2011). Structured methodology for supplier selection and evaluation in a supply chain. *Information Sciences*, 181(9), 1651–1670. <https://doi.org/10.1016/j.ins.2010.07.026>
- Chou, S.-Y., & Chang, Y.-H. (2008). A decision support system for supplier selection based on a strategy-aligned fuzzy SMART approach. *Expert Systems with Applications*, 34(4), 2241–2253. <https://doi.org/10.1016/j.eswa.2007.03.001>
- Ellram, L. M. (1990). The supplier selection decision in strategic partnerships. *Journal of Purchasing and Materials Management*, 26(4), 8–14
- Er Kara, M., & Firat, S. Ü. O. (2018). Supplier risk assessment based on best-worst method and K-means clustering: A case study. *Sustainability*, 10(4), 1066. <https://doi.org/10.3390/su10041066>
- Fathi, M. R., Khosravi, A., & Esmaeelbeigi, F. (2025). Modelling the barriers to blockchain adoption in tourism industry based on ISM and Fuzzy DEMATEL approach. *Journal of Data Analytics and Intelligent Decision-making*, 1(4), 50–80. <https://doi.org/10.22091/jdaid.2026.14797.1027>
- Frank, E., Hall, M. A., & Witten, I. H. (2016). *The WEKA workbench: Online appendix for data mining: Practical machine learning tools and techniques* (4th ed.). Morgan Kaufmann.
- García, N., Puente, J., Fernández, I., & Priore, P. (2013). Supplier selection model for commodities procurement: Optimised assessment using a fuzzy decision support system. *Applied Soft Computing*, 13(4), 1939–1951. <https://doi.org/10.1016/j.asoc.2012.12.004>

- Goftari, E., Carias, J. R., Fulford, L., & Li, H. (2026). Post-Wildfire Indoor Pollution in WUI Areas following the 2025 Los Angeles Fires. Part I. Establishing Baseline Contaminant Levels Prior to Home Reoccupation. *ACS Es&t Air*, 3(1), 142-155. <https://doi.org/10.1021/acsestair.5c00281>
- Goh, M., Lim, J. Y. S., & Meng, F. (2007). A stochastic model for risk management in global supply chain networks. *European Journal of Operational Research*, 182(1), 164–173. <https://doi.org/10.1016/j.ejor.2006.07.036>
- Govindan, K., Rajendran, S., Sarkis, J., & Murugesan, P. (2015). Multi criteria decision making approaches for green supplier evaluation and selection: A literature review. *Journal of Cleaner Production*, 98, 66–83. <https://doi.org/10.1016/j.jclepro.2013.06.046>
- Guo, C., & Li, X. (2014). A multi-echelon inventory system with supplier selection and order allocation under stochastic demand. *International Journal of Production Economics*, 151, 37–47. <https://doi.org/10.1016/j.ijpe.2014.01.017>
- Ha, S. H., & Krishnan, R. (2008). A hybrid approach to supplier selection for the maintenance of a competitive supply chain. *Expert Systems with Applications*, 34(2), 1303–1311. <https://doi.org/10.1016/j.eswa.2006.12.008>
- Haghighi, P. S., Moradi, M., & Salahi, M. (2014). Supplier segmentation using fuzzy linguistic preference relations and fuzzy clustering. *International Journal of Intelligent Systems and Applications*, 6(5), 76–84. <https://doi.org/10.5815/ijisa.2014.05.10>
- Haghighi, P. S., Moradi, M., & Salahi, M. (2014). Supplier segmentation using fuzzy linguistic preference relations and fuzzy clustering. *International Journal of Intelligent Systems and Applications*, 6(5), 76
- Haghshenas Nasrabadi, A., & Ghasemy Yaghin, R. (2025). The role of data quality and visibility in risk management and performance optimization in the downstream supply chain. *Journal of Data Analytics and Intelligent Decision-making*, 1(1), 23-32. <https://doi.org/10.22091/jdaid.2025.14090.1005>
- Hallikas, J., Karvonen, I., Pulkkinen, U., Virolainen, V. M., & Tuominen, M. (2004). Risk management processes in supplier networks. *International Journal of Production Economics*, 90(1), 47–58. <https://doi.org/10.1016/j.ijpe.2004.02.007>
- Hamdi, F., Ghorbel, A., Masmoudi, F., & Dupont, L. (2018). Optimization of a supply portfolio in the context of supply chain risk management: Literature review. *Journal of Intelligent Manufacturing*, 29(4), 763–788. <https://doi.org/10.1007/s10845-015-1143-y>
- Häntsch, M., & Huchzermeier, A. (2013). Identifying, analyzing, and assessing risk in the strategic planning of a production network: The practical view of a German car manufacturer. *Journal of Management Control*, 24(2), 125–158. <https://doi.org/10.1007/s00187-013-0173-1>
- Haq, A. N., & Kannan, G. (2006). Fuzzy analytical hierarchy process for evaluating and selecting a vendor in a supply chain model. *The International Journal of Advanced Manufacturing Technology*, 29(7–8), 826–835. <https://doi.org/10.1007/s00170-005-2562-8>
- Heidari, B., Myint, S. W., & Zhu, Y. (2025). Examining environmental stress changes in response to climate change and land use dynamics in the Colorado River Basin over the past two decades. *Sustainable Futures*, 10, 101427. <https://doi.org/10.1016/j.sftr.2025.101427>
- Heidarzade, A., Mahdavi, I., & Mahdavi-Amiri, N. (2016). Supplier selection using a clustering method based on a new distance for interval type-2 fuzzy sets: A case study. *Applied Soft Computing*, 38, 213–231. <https://doi.org/10.1016/j.asoc.2015.09.030>
- Ho, W., Xu, X., & Dey, P. K. (2010). Multi-criteria decision-making approaches for supplier evaluation and selection: A literature review. *European Journal of Operational Research*, 202(1), 16–24. <https://doi.org/10.1016/j.ejor.2009.05.009>
- Hong, G. H., Park, S. C., Jang, D. S., & Rho, H. M. (2005). An effective supplier selection method for constructing a competitive supply-relationship. *Expert Systems with Applications*, 28(4), 629–639. <https://doi.org/10.1016/j.eswa.2004.12.003>
- Hou, J., & Su, D. (2007). EJB-MVC oriented supplier selection system for mass customization. *Journal of Manufacturing Technology Management*, 18(1), 54–71. <https://doi.org/10.1108/17410380710717151>

- Jain, A. K. (2010). Data clustering: 50 years beyond K-means. *Pattern Recognition Letters*, 31(8), 651–666. <https://doi.org/10.1016/j.patrec.2009.09.011>
- Jain, V., Sangaiah, A. K., Sakhuja, S., Thoduka, N., & Aggarwal, R. (2018). Supplier selection using fuzzy AHP and TOPSIS: A case study in the Indian automotive industry. *Neural Computing and Applications*, 29(7), 555–564. <https://doi.org/10.1007/s00521-016-2532-7>
- Junior, F. R. L., Osiro, L., & Carpinetti, L. C. R. (2014). A comparison between Fuzzy AHP and Fuzzy TOPSIS methods to supplier selection. *Applied Soft Computing*, 21, 194–209. <https://doi.org/10.1016/j.asoc.2014.03.014>
- Karpak, B., Kumcu, E., & Kasuganti, R. R. (2001). Purchasing materials in the supply chain: Managing a multi-objective task. *European Journal of Purchasing & Supply Management*, 7(3), 209–216. [https://doi.org/10.1016/S0969-7012\(00\)00015-6](https://doi.org/10.1016/S0969-7012(00)00015-6)
- Keskin, G. A., İlhan, S., & Özkan, C. (2010). The Fuzzy ART algorithm: A categorization method for supplier evaluation and selection. *Expert Systems with Applications*, 37(2), 1235–1240. <https://doi.org/10.1016/j.eswa.2009.06.039>
- Khaleie, S., Fasanghari, M., & Tavassoli, E. (2012). Supplier selection using a novel intuitionist fuzzy clustering approach. *Applied Soft Computing*, 12(6), 1741–1754. <https://doi.org/10.1016/j.asoc.2012.01.005>
- Kolour, H. R., Momayezi, V., & Momayezi, F. (2026). Enhancing supplier selection in public manufacturing: A hybrid multi-criteria decision-making approach. *Spectrum of Decision Making and Applications*, 3(1), 1–20.
- Krajewski, L. J. (2001). *Operations management: Strategy and SimQuick package*. Pearson College Division.
- Kull, T. J., & Talluri, S. (2008). A supply risk reduction model using integrated multicriteria decision making. *IEEE Transactions on Engineering Management*, 55(3), 409–419. <https://doi.org/10.1109/TEM.2008.922627>
- Kuo, T.-C., Hsu, C.-W., & Li, J.-Y. (2015). Developing a green supplier selection model by using the DANP with VIKOR. *Sustainability*, 7(2), 1661–1689. <https://doi.org/10.3390/su7021661>
- Levary, R. R. (2008). Using the analytic hierarchy process to rank foreign suppliers based on supply risks. *Computers & Industrial Engineering*, 55(2), 535–542. <https://doi.org/10.1016/j.cie.2007.12.004>
- Liao, Z., & Rittscher, J. (2007). A multi-objective supplier selection model under stochastic demand conditions. *International Journal of Production Economics*, 105(1), 150–159. <https://doi.org/10.1016/j.ijpe.2006.03.001>
- Luan, J., Yao, Z., Zhao, F., & Song, X. (2019). A novel method to solve supplier selection problem: Hybrid algorithm of genetic algorithm and ant colony optimization. *Mathematics and Computers in Simulation*, 156, 294–309. <https://doi.org/10.1016/j.matcom.2018.10.003>
- Maghsoodi, A. I., Kavian, A., Khalilzadeh, M., & Brauers, W. K. M. (2018). CLUS-MCDA: A novel framework based on cluster analysis and multiple criteria decision theory in a supplier selection problem. *Computers & Industrial Engineering*, 118, 409–422. <https://doi.org/10.1016/j.cie.2018.03.011>
- Mavi, R. K., Goh, M., & Mavi, N. K. (2016). Supplier selection with Shannon entropy and fuzzy TOPSIS in the context of supply chain risk management. *Procedia - Social and Behavioral Sciences*, 235, 216–225. <https://doi.org/10.1016/j.sbspro.2016.11.017>
- Micheli, G. J. L., Cagno, E., & Di Giulio, A. (2009). Reducing the total cost of supply through risk-efficiency-based supplier selection in the EPC industry. *Journal of Purchasing and Supply Management*, 15(3), 166–177. <https://doi.org/10.1016/j.pursup.2009.02.002>
- Mohammadi Motlagh, H., Mohammadi Motlagh, A., & Rezaee Noor, J. (2015). Design an expert system for evaluation and selection supplier. *Industrial Management Journal*, 7(2), 385–403.
- Mohammed, A., Bai, C., Channouf, N., Ahmed, T. A., & Mohamed, S. M. (2023). G-resilient multi-tier supplier selection and order allocation in food industry: A hybrid methodology. *International Journal of Systems Science: Operations & Logistics*, 10(1). <https://doi.org/10.1080/23302674.2023.2195055>
- Muralidharan, C., Anantharaman, N., & Deshmukh, S. G. (2002). A multi-criteria group decision-making model for supplier rating. *Journal of Supply Chain Management*, 38(4), 22–33. <https://doi.org/10.1111/j.1745-493X.2002.tb00141.x>
- Nekooie, M. A., Sheikhalishahi, M., & Hosnavi, R. (2015). Supplier selection considering strategic and operational risks: A combined qualitative and quantitative approach. *Production Engineering*, 9(5), 665–673. <https://doi.org/10.1007/s11740-015-0635-4>

- Parkouhi, S. V., Ghadikolaei, A. S., & Lajimi, H. R. F. (2019). Resilient supplier selection and segmentation in grey environment. *Journal of Cleaner Production*, 207, 1123–1137. <https://doi.org/10.1016/j.jclepro.2018.10.003>
- Paul, S. K. (2015). Supplier selection for managing supply risks in supply chain: A fuzzy approach. *The International Journal of Advanced Manufacturing Technology*, 79(1–4), 657–664. <https://doi.org/10.1007/s00170-015-6833-z>
- Pitchipoo, P., Venkumar, P., & Rajakarunakaran, S. (2012). A distinct decision model for the evaluation and selection of a supplier for a chemical processing industry. *International Journal of Production Research*, 50(16), 4635–4648. <https://doi.org/10.1080/00207543.2011.599348>
- Pokharel, S. (2008). A two-objective model for decision making in a supply chain. *International Journal of Production Economics*, 111(2), 378–388. <https://doi.org/10.1016/j.ijpe.2007.01.006>
- Punniyamoorthy, M., Mathiyalagan, P., & Parthiban, P. (2011). A strategic model using structural equation modeling and fuzzy logic in supplier selection. *Expert Systems with Applications*, 38(1), 458–474. <https://doi.org/10.1016/j.eswa.2010.06.086>
- Rao, C., Xiao, X., Goh, M., Zheng, J., & Wen, J. (2017). Compound mechanism design of supplier selection based on multi-attribute auction and risk management of supply chain. *Computers & Industrial Engineering*, 105, 63–75. <https://doi.org/10.1016/j.cie.2016.12.038>
- Ravindran, A. R., Ufuk Bilsel, R., Wadhwa, V., & Yang, T. (2010). Risk adjusted multicriteria supplier selection models with applications. *International Journal of Production Research*, 48(2), 405–424. <https://doi.org/10.1080/00207540903175072>
- Rezaei, J. (2015). Best-worst multi-criteria decision-making method. *Omega*, 53, 49–57. <https://doi.org/10.1016/j.omega.2014.11.009>
- Rezaei, J., & Ortt, R. (2013). Multi-criteria supplier segmentation using a fuzzy preference relations based AHP. *European Journal of Operational Research*, 225(1), 75–84. <https://doi.org/10.1016/j.ejor.2012.09.037>
- Rezaei, J., Nispeling, T., Sarkis, J., & Tavasszy, L. (2016). A supplier selection life cycle approach integrating traditional and environmental criteria using the best worst method. *Journal of Cleaner Production*, 135, 577–588. <https://doi.org/10.1016/j.jclepro.2016.06.125>
- Rezaei, J., Wang, J., & Tavasszy, L. (2015). Linking supplier development to supplier segmentation using Best Worst Method. *Expert Systems with Applications*, 42(23), 9152–9164. <https://doi.org/10.1016/j.eswa.2015.07.073>
- Rukhsar, M., Hussain, A., Ullah, K., Moslem, S., & Senapati, T. (2025). Intelligent decision analysis for green supplier selection with multiple attributes using circular intuitionistic fuzzy information aggregation and Frank triangular norms. *Energy Reports*, 13, 5773–5791.
- Şahin, Y., & Supçiller, A. (2015). Tedarikçi seçimi için bir karar destek sistemi. *Mühendislik Bilimleri ve Tasarım Dergisi*, 3(2), 91–104.
- Sarkis, J., & Talluri, S. (2002). A model for strategic supplier selection. *Journal of Supply Chain Management*, 38(1), 18–28. <https://doi.org/10.1111/j.1745-493X.2002.tb00117.x>
- Schoenherr, T., Tummala, V. M. R., & Harrison, T. P. (2008). Assessing supply chain risks with the analytic hierarchy process: Providing decision support for the offshoring decision by a US manufacturing company. *Journal of Purchasing and Supply Management*, 14(2), 100–111. <https://doi.org/10.1016/j.pursup.2008.01.004>
- Scott, J., Ho, W., Dey, P. K., & Talluri, S. (2015). A decision support system for supplier selection and order allocation in stochastic, multi-stakeholder and multi-criteria environments. *International Journal of Production Economics*, 166, 226–237. <https://doi.org/10.1016/j.ijpe.2014.11.008>
- Senvar, Ö., Tuzkaya, G., & Kahraman, C. (2014). Multi criteria supplier selection using fuzzy PROMETHEE method. In C. Kahraman & Ö. Kabak (Eds.), *Supply chain management under fuzziness* (pp. 21–34). Springer. https://doi.org/10.1007/978-3-642-53939-8_2
- Shemshadi, A., Toreihi, M., & Shirazi, H. (2011). Supplier selection based on supplier risk: An ANP and fuzzy TOPSIS approach. *International Journal of Advanced Manufacturing Technology*, 11–121.

- Sithi, S. S., Ara, M. A., Dhruvo, A. T., et al. (2025). Sustainable supplier selection in the textile industry using triple bottom line and SWARA-TOPSIS approaches. *Discover Sustainability*, 6, 344. <https://doi.org/10.1007/s43621-025-01206-9>
- Song, W., Ming, X., & Liu, H.-C. (2017). Identifying critical risk factors of sustainable supply chain management: A rough strength-relation analysis method. *Journal of Cleaner Production*, 143, 100–115. <https://doi.org/10.1016/j.jclepro.2016.12.145>
- Tang, C. S. (2006). Perspectives in supply chain risk management. *International Journal of Production Economics*, 103(2), 451–488. <https://doi.org/10.1016/j.ijpe.2005.12.006>
- Torabi, S. A., Baghersad, M., & Mansouri, S. A. (2015). Resilient supplier selection and order allocation under operational and disruption risks. *Transportation Research Part E: Logistics and Transportation Review*, 79, 22–48. <https://doi.org/10.1016/j.tre.2015.03.005>
- Torres-Ruiz, A., & Ravindran, A. R. (2018). Multiple criteria framework for the sustainability risk assessment of a supplier portfolio. *Journal of Cleaner Production*, 172, 4478–4493. <https://doi.org/10.1016/j.jclepro.2017.05.049>
- Tricaud, C., & Chen, Y. Q. (2010). An approximate method for numerically solving fractional order optimal control problems of general form. *Computers & Mathematics with Applications*, 59(5), 1644–1655. <https://doi.org/10.1016/j.camwa.2009.08.029>
- Vanany, I., Zailani, S., & Pujawan, N. (2009). Supply chain risk management: Literature review and future research. *International Journal of Information Systems and Supply Chain Management*, 2(1), 16–33. <https://doi.org/10.4018/jisscm.2009010102>
- Vickers, N. J. (2017). Animal communication: When I'm calling you, will you answer too? *Current Biology*, 27(14), R713–R715. <https://doi.org/10.1016/j.cub.2017.06.037>
- Wetzstein, A., Hartmann, E., Benton, W. C., & Hohenstein, N.-O. (2019). Uncovering the supplier selection knowledge structure: A systematic citation network analysis from 1991 to 2017. *Journal of Purchasing and Supply Management*, 25(4), 100519. <https://doi.org/10.1016/j.pursup.2018.10.002>
- Wetzstein, A., Hartmann, E., Benton, W. C., & Hohenstein, N.-O. (2016). A systematic assessment of supplier selection literature: State-of-the-art and future scope. *International Journal of Production Economics*, 182, 304–323. <https://doi.org/10.1016/j.ijpe.2016.06.022>
- Wu, T., Blackhurst, J., & Chidambaram, V. (2007). AIDEA: A methodology for supplier evaluation and selection in a supplier-based manufacturing environment. *International Journal of Manufacturing Technology and Management*, 11(2), 174–192. <https://doi.org/10.1504/IJMTM.2007.013487>
- Xiao, Z., Chen, W., & Li, L. (2012). An integrated FCM and fuzzy soft set for supplier selection problem based on risk evaluation. *Applied Mathematical Modelling*, 36(4), 1444–1454. <https://doi.org/10.1016/j.apm.2011.09.014>
- You, X.-Y., You, J.-X., Liu, H.-C., & Zhen, L. (2015). Group multi-criteria supplier selection using an extended VIKOR method with interval 2-tuple linguistic information. *Expert Systems with Applications*, 42(4), 1906–1916. <https://doi.org/10.1016/j.eswa.2014.10.004>
- Zanakis, S. H., Solomon, A., Wishart, N., & Dubish, S. (1998). Multi-attribute decision making: A simulation comparison of select methods. *European Journal of Operational Research*, 107(3), 507–529. [https://doi.org/10.1016/S0377-2217\(97\)00147-1](https://doi.org/10.1016/S0377-2217(97)00147-1)
- Zhang, X., Zhang, C., Zhou, Y., & Wang, S. (2006). Supplier categorization with K-means type subspace clustering. In *Asia-Pacific Web Conference 2006* (pp. 507–516). Springer. https://doi.org/10.1007/11760023_58
- Zouggari, A., & Benyoucef, L. (2012). Simulation based fuzzy TOPSIS approach for group multi-criteria supplier selection problem. *Engineering Applications of Artificial Intelligence*, 25(3), 507–519. <https://doi.org/10.1016/j.engappai.2011.09.008>