TÜRKİYE CUMHURİYETİ
ADANA ALPARSLAN TÜRKEŞ SCIENCE AND TECHNOLOGY UNIVERSITY

GRADUATE SCHOOL
INDUSTRIAL ENGINEERING DEPARTMENT

AN INTEGRATED PRINCIPAL COMPONENT ANALYSIS AND MULTI-CRITERIA DECISION-MAKING APPROACH FOR SUPPLIER SELECTION IN THE GARMENT SUPPLY CHAIN

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M.Sc.

ADANA, 2024

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CERTIFICATION OF APPROVAL

(AN INTEGRATED PRINCIPAL COMPONENT ANALYSIS AND MULTI-CRITERIA DECISION-MAKING APPROACH FOR SUPPLIER SELECTION IN THE GARMENT SUPPLY CHAIN)

This **M.Sc.** thesis, **completed under the conditions determined by the relevant regulations**, by **Tuğba Saraç Işıl with student number** 20800701004 in **Adana Alparslan Türkeş Science and Technology University Institute of Graduate School** Indistrual Engineering **Department**, has been evaluated by the following academic committee, and approved in accordance with the relevant articles of the "Adana Alparslan Türkeş Science and Technology University Graduate Education Regulations".

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DECLARATION OF CONFORMITY

In this thesis study, which was prepared following the thesis writing rules of Adana Alparslan Türkeş Science and Technology University Institute of Graduate School, I declare that I provide all the information, documents, evaluations and results in accordance with scientific ethics and moral codes without resorting to any means or assistance that would be contrary to scientific ethics and traditions. I also declare that I refer to all of the articles I used in this study with appropriate references and accept all moral and legal consequences if a Scenario is found contrary to my statement regarding my work.

22/04/2024

[Signature]

Tuğba SARAÇ IŞIL

ÖZET

HAZIR GİYİM TEDARİK ZİNCİRİNDE TEDARİKÇİ SEÇİMİ İÇİN ENTEGRE TEMEL BİLEŞEN ANALİZİ VE ÇOK KRİTERLİ KARAR VERME YAKLAŞIMI

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Tedarik zinciri yönetiminin önemli aşamalarından biri de tedarikçi seçimidir. Tedarikçi seçimi işletmelerin karşılaştığı en temel sorunlardan biridir. Günümüzde artan rekabet sebebiyle işletmeler tedarikçi seçimi problemlerine önem vermeye başlamıştır. Uzun vadede sürdürülebilir ilişkiler sağlamak için çeşitli çalışmalara odaklanmaktadırlar.

Bu çalışma, hazır giyim sektöründe en uygun tedarikçiyi seçmek için hibrit bir yaklaşım sunmaktadır. Öncelikle kriter azaltmak için Temel Bileşenler Analizi (PCA) yöntemi uygulanmıştır. Daha sonra entropi ile kriter ağırlıkları hesaplanmıştır. Son olarak İdeal Sonuç Odaklı Çok Ölçütlü Karar Verme (TOPSIS) yöntemi ile kriterler sıralanmıştır. Sıralamaya göre en uygun tedarikçi seçilmiştir. Ağırlıklara bağlı olarak kriterlerdeki değişikliklerin etkisini değerlendirmek için duyarlılık analizi kullanılmıştır. Kriter azaltma yapılmadan EWM-TOPSIS ve Çok Kriterli Karar Verme İçin Karmaşık Sıralama (VIKOR) yöntemi ile karşılaştırılmıştır. Önerilen model ile hazır giyim üreticilerinin işletmeleri için birçok yönden daha uygun tedarikçiyi belirleme fırsatı sunacaktır.

Anahtar Kelimeler: Hazır giyim, Temel Bileşenler Analizi, TOPSIS, Tedarikçi seçimi

ABSTRACT

AN INTEGRATED PRINCIPAL COMPONENT ANALYSIS AND MULTI-CRITERIA DECISION-MAKING APPROACH FOR SUPPLIER SELECTION IN THE GARMENT SUPPLY CHAIN

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One of the important stages of Supply Chain Management (SCM) is supplier selection. SS is one of main problems encountered by businesses. Due to increasing competition today, businesses have begun to attach importance to SS problems. They focus on various studies to ensure sustainable relationships in the long term.

This study presents a hybrid approach to selecting the most suitable supplier in the garment industry. First, the Principal Component Analysis (PCA) method was applied to reduce the criterion. Then, the criterion weights were calculated with entropy. Finally, the criteria were ranked with the Technique for Order Preference by Similarity to An Ideal Solution (TOPSIS) method. The most suitable supplier was selected according to the ranking. Sensitivity analysis was employed to assess the impact of criteria changes depending on the weights. It was compared with EWM-TOPSIS and VIseKriterijumsa Optimizacija I Kompromisno Resenje, Elimination and Choice Translating Reality (VIKOR) method without criteria reduction. The proposed model will provide the opportunity to determine a more suitable supplier in many aspects for businesses of garment manufacturers.

Keywords: Garment, Principal Component Analysis, TOPSIS, Supplier Selection

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LIST OF ABBREVIATIONS

AHP	: Analytic Hierarchy Process
AI	: Artificial Intelligence
BWM	: Best Worst Method
CM	: Cloud Model
COPRAS	: Complex Proportional Assessment
DEA	: Data Envelopment Analysis
DEMATEL	: Decision-Making Trial and Evaluation Laboratory
FST	: Fuzzy Set Theory
GRA	: Grey Relational Analysis
IFS	: Intuitionistic Fuzzy Set
MCDM	: Multi-Criteria Decision Making
MILP	: Mixed Integer Linear Programming
MP	: Mathematical Programming
PCA	: Principal Component Analysis
PROMETHEE	: Preference Ranking Organization Method for Enrichment Evaluation
SCM	: Supply Chain Management
SCOR	: Supply Chain Operation Reference
SEM	: Structural Equation Modeling
SPSS	: Statistical Package for the Social Sciences
SS	: Supplier Selection
TFN	: Triangular Fuzzy Numbers
TFT LCD	: Thin-film-transistor Liquid-crystal display
TOPSIS	: Technique for Order Preference by Similarity to an Ideal Solution
VIKOR	: VIseKriterijumsa Optimizacija I Kompromisno Resenje, Elimination and Choice Translating Reality
WASPAS	: Weighted Aggregated Sum Product Assessment

LIST OF SYMBOLS

C_1	: Quality
C_2	: Price
C_3	: Location
C_4	: Lead-time
C_5	: Monetary position
C_6	: Financial position
C_7	: On-time delivery
C_8	: Ability to product change
C_9	: Support and service
C_{10}	: Technical Capacity

1. INTRODUCTION

The garment industry started to develop especially after the 1980s. The investments in the garment sector and the regulations on exports at this time contributed to this development. The contribution of the sector to the Turkish economy is very important. It is an export-oriented sector, and the capacity of the country's garment industry is greater than the demand. As of 2021, it ranks sixth in the world's garment rankings. Most of the enterprises producing in the sector are small and medium-sized enterprises. According to the Social Security Institution's December 2021 data, there are 74,946 companies producing clothing in the country. The Turkish garment industry has a wide product range and has advantages such as experience, knowledge, and quality.

SCM in the garment industry is a long process that starts from the design of the products to the delivery of the products to the consumer. Nowadays, there is competition and rapid change in the garment industry due to globalization, the development of technology, and consumerism. It is very important to keep up with fashion trends and meet consumer demands in this sector. Innovation and continuous improvement are among the areas of work that should be focused on for businesses that aim to meet these demands. Also, apparel SCM includes disciplines such as SS, technology, sustainability, risk management, demand management, and trend analysis.

SCM and SS began to develop as of the Industrial Revolution. With the industrial revolution, the processes of the supply chain have become more complex with the increase in production and the need for raw materials. Later, it evolved due to reasons such as the increase in production, development of technology, globalization, and pandemic. It has now become an inevitable strategic importance for businesses.

The supply chain covers all activities from the procurement stage of goods and services until they reach the consumer. It includes very comprehensive processes such as supply of raw materials, production, logistics, storage, inventory management, and distribution. Nowadays, due to the increase in competition with globalization, more importance has started to be given to SCM. Businesses want to keep up with this competitive environment. Because of these desires, they are turning to development and improvement in SCM. A well-managed supply chain has made it easier to adapt to changing conditions. The main purpose of the supply chain is to increase profits by reducing costs. In addition, it aims to keep strong relationships, satisfy customers, become a competitive business, have a flexible structure that easily adapts to conditions, always increase efficiency and profitability, and be a sustainable and image-conscious business.

SS is the collaboration to provide a good or service. It is the selection of suppliers that meet the determined criteria among the alternatives to provide the necessary supply. The main purpose of SS is to reduce costs and increase efficiency and profit. It is desirable to ensure strong and sustainable relationships. While choosing the right supplier provides many benefits, choosing the wrong supplier can cause disruptions in many processes. The effectiveness of units such as production, logistics, and purchasing are in question. It is possible to select suppliers using several methods: Cost-based Model, Mathematical Programming (MP) Model, Statistical Models (SM), Artificial Intelligence (AI) Models, Multi Criteria Decision Making (MCDM) Models.

Although the criteria taken into consideration in SS processes are similar to those in other sectors, the importance given to each criterion may vary. While factors such as price, quality, delivery time, and transportation have been effective for many years, social, environmental, and competitive factors have also been effective recently. Communication skills, employee training, company image, impression, business desire, environmental management system, recycling, pollution control, legal compliance, attitude, etc.

MCDM is one of the methods used for selection purposes, as in the SS method. It emerged after the 1950s. It was needed due to the difficulty in decision-making processes. It is used to choose the most suitable one among many alternatives according to the criteria. The method includes many methods, so it can be examined under many headings. Analytical Hierarchy Process (AHP), TOPSIS, VIKOR are some of them. It is seen that MCDM has been used in many theoretical studies or operating businesses in the past or today. Software programs can be used for calculations, or they can be calculated manually. It is also used in different areas. In the academic field, such as industry, economy, and production.

In this study, the SS problem in apparel SCM is discussed. A hybrid method that is thought to be a solution to the problem has been applied. Thus, an alternative approach that can be used by businesses when selecting suppliers will be proposed. PCA is used to reduce dependency and the number of criteria, entropy is used to weight the criteria and the TOPSIS method is used to choose between alternatives. This is related to the proximity of the best solution to the positive ideal solution. The solution closest to the positive ideal solution is the best solution. Many past and present studies have used this approach, proving its ongoing effectiveness.

The other chapters of the thesis continue as follows. In Section 2, other studies related to supplier selection in the literature are reviewed and summarized. In Section 3, information on supplier selection and multi-criteria decision-making methods is presented. Section 4 presents the results of the model created using data from the garment industry. Finally, in section 5, explanations about the results are given.

2. LITERATURE REVIEW

Considerable research has been done on SS as a business strategy, particularly in the modern era. Studies reveal the importance of the SS process for the performance of businesses. On this topic, numerous research, practical, and hybrid approaches have been developed. MCDM is one of these methods and has been included in many studies. A literature review was conducted including MCDM and other selection methods. Various studies conducted for SS are summarized below:

Lee et al. (2009) presented a model for evaluating green suppliers. The Delphi method was first implemented to distinguish traditional suppliers’ and green suppliers’ evaluation criteria. For an anonymous thin-film-transistor liquid-crystal display (TFT LCD) manufacturer in Taiwan, a Fuzzy Extended AHP model was created based on the hierarchy to evaluate green suppliers, and the most suitable supplier was selected.

Bali et al. (2013) proposed an integrated MCDM approach based on an Intuitionistic Fuzzy Set (IFS) and Grey Relational Analysis (GRA), consisting of eight steps for the green SS problem. Some of the frequently encountered criteria for green SS were suggested. IFS and GRA were used because of the uncertainty of decision-makers' evaluations and the subjectivity of the criteria. The novelty of the study is that instead of representing the whole selection process with the same uncertainty theory, appropriate uncertainty methods are used at different steps. Intuitionistic fuzzy entropy was used to calculate the entropy weights of the criteria and GRA was used to find the most suitable alternative. An example was presented to an automobile company. The results showed that Fuzzy Set Theory (FST) and gray theory can be used together.

Zhao et al. (2014) presented a hybrid fuzzy multi-attribute decision-making approach to select the appropriate green thermal power equipment supplier. The fuzzy entropy-TOPSIS method was used. FST was applied to transform linguistic preferences into Triangular Fuzzy Numbers (TFN). The fuzzy entropy weighting method was used to determine criterion weights. Fuzzy TOPSIS was used to rank all suppliers of environmentally friendly thermal power equipment. Appropriate green thermal power equipment was selected, which contributes to promoting the company's sustainable development, and the sustainability of China's electric power industry.

Banaeian et al. (2015) presented an applicable methodology for green SS in the food industry. 10 SS criteria were determined and ranked according to the evaluation factor. Potential suppliers were evaluated according to high degree criteria, and group decision-making is practiced using fuzzy and gray set theories. An example of edible oil industry packaging material SS was given.

Javad et al. (2020) aimed to select Khouzestan Steel Company suppliers according to their green innovation capabilities. The Best-Worst Method was used to rank the various criteria, and the Fuzzy TOPSIS method was used to rank the alternative suppliers. The most suitable green supplier was selected from 11 suppliers. Finally, sensitivity analysis was performed to check the robustness of the presented SS framework.

Kuo et al. (2015) presented a new study to realize green SS. The information considered in this study was derived from a selected electronics corporation. 17 criteria were determined in two dimensions regarding the environment and management systems. In this SS study, the Decision-Making Trial and Evaluation Laboratory (DEMATEL), the Analytic Network Process (ANP), and the VIKOR method were included. A case study was included. This study was related to the electronics industry.

Yazdani et al. (2017) introduced an integrated approach for green SS. While establishing a relationship structure, mutual relations between customer requirements were handled with the help of DEMATEL method. The Quality Function Deployment (QFD) model used a central relationship matrix to determine the degree of relationship between customer requirements for each pair of SS criteria. Complex Proportional Assessment (COPRAS) was used to prioritize and rank alternative suppliers. A case study was presented for an Iranian dairy company.

Quan et al. (2018) proposed a hybrid MCDM approach for green SS in a large group setting. Range-valued heuristic ambiguous language sets were applied to evaluate the green suppliers' performance about each criterion. Ant Colony Algorithm was used to subdivide decision makers. The extended multi-objective optimization by ratio analysis approach was applied to build the ranking of alternative suppliers. An example of a real estate company was shown.

Abdullah et al. (2019) proposed a choice of green suppliers using the Preference Ranking Organization Method (PROM) for enrichment evaluation under the usual criteria preference functions. Seven economic and environmental criteria, four suppliers, and five decision-makers were determined. Data was collected through personal communication with decision-makers. Under the usual criteria function, the algorithm of Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) was applied, and the most preferred alternative supplier was selected.

Yildiz (2019) aimed to select the best green supplier for a large-scale company in the automotive supplier industry that exports most of its products. Green SS criteria were determined with a team of four people working in the quality, logistics, and purchasing departments. Five alternative green suppliers were evaluated using the TOPSIS method according to the criteria. It was observed that the results were sensitive according to the criteria and alternatives used in the study.

Masoomi et al. (2022) used the fuzzy Best Worst Method (BWM) along with COPRAS, Weighted Aggregated Sum Product Assessment (WASPAS) to evaluate many strategic suppliers in a sustainable supply chain. Through literature review, they identified nine strategic SS criteria. An integrated binary contrast matrix was drawn to sum the weights using fuzzy BWM. The criteria with the highest weights were then used as input in other methods to select the appropriate replacement. Two good methods for analyzing supplier clusters were combined. In the form of fuzzy BWM-fuzzy COPRAS and fuzzy BWM-fuzzy WASPAS. Consistency testing was conducted to examine the opinions of professionals. Sensitivity Analysis was performed to ensure the robustness of the framework. They conducted a case study of Iran's renewable energy supply chain. The introduced framework was found reliable thanks to the example. The proposed framework provides advantages such as systematically calculating the weights of attributes, capturing uncertainty in preferences, and reducing inaccuracies in decision-making. It reduced subjective randomness caused by human intervention.

Lu et al. (2019) presented SS in the biomass industry. They identified the problems encountered by SS. They tried to find ways to make improvements to solve their problems. To demonstrate the effectiveness of the proposed model, green SS in the straw biomass industry in China was addressed. The Cloud Model (CM) was proposed to resolve the blurriness and randomness of evaluation information. The CM was applied to transform the information of linguistic variables into the information of the number of intervals. An index system consisting of four criteria was created. These four criteria were also divided into subcriteria. Fuzzy AHP was used to determine the index weight. In the example, alternatives were evaluated and ranked according to the index system. A decision framework based on the CM and probability degree was created for the selection of the most suitable green supplier. Sensitivity analysis was performed. The model was suitable for finding a more suitable green supplier.

Khattak et al. (2022) addressed a textile supply chain problem for supplying textile dyestuff products. A multi-objective interactive fuzzy programming model has been developed. They determined four green parameters. They used an environmental scale for green parameters. All suppliers were scored on this scale. A fuzzy language scale and triangular membership were used. Each objective function was solved separately. It was then used as a constraint for other purposes. The green score ranking was kept as a constraint to select suppliers with the highest green score. Thanks to fuzzy membership, satisfaction levels were calculated for each parameter using the data of the textile industry in the example.

Sun and Cai (2021) tried to solve the green SS problem. They used it to integrate TOPSIS and GRA methods to rank alternatives. They extended this hybrid TOPSIS and GRA method in the single-valued neutrosophic environment. During the SS process, the weights assigned by various experts were taken into consideration to make an informed decision.

Singh et al. (2018) presented a new framework for the selection of eco-friendly cattle suppliers based on Big Data Cloud Computing Technology. With the fuzzy AHP and DEMATEL, the weight was given according to the priority of the customers and the slaughterhouse & processor quality inspector. The fuzzy TOPSIS method generated a ranking list for suppliers.

Valipour Parkouhi et al. (2019) considered two dimensions, stamina-enhancing, and stamina-reducing, to select and segment suppliers. The Grey DEMATEL method was used to determine the importance degree of the criteria for each of these two dimensions. Each supplier's score according to each dimension was determined by Grey Simple Additive Weighting (SAW). The most important reducing and the most important increasing criteria were selected. Strategies were presented to develop suppliers and drive them towards flexibility.

Garg (2021) wrote a research article on e-supplier criteria selection methods. This article contained a review of 39 research articles published between 2005 and 2020. Many methods have been used on the subject in literature. Structural Equation Modeling (SEM) was applied to evaluate the impact of each factor. The weight of each criterion was calculated. It presented the importance of criteria selection in e-SS for an organization. The study used the Indian manufacturing industry as an example. The proposed system can be integrated by considering the different criteria of each industry.

Rahman et al. (2022) used MCDM for sustainable SS in the textile dyeing industry. Bangladesh textile dyeing industry was addressed as an example. 15 evaluation criteria were determined. The weights of the determined criteria were determined with Stepwise Weight Assessment Ratio Analysis (SWARA). The WASPAS method was used to determine the final ranking of suppliers. As a result, the most important criterion was chosen as chemical quality. This method showed that supplier A was the most sustainable supplier. The results were compared with different MCDM methods.

Davoudabadi et al. (2020) presented a new approach to analyze the flexible SS problem. Criteria were identified and used by integrating Data Envelopment Analysis (DEA) and entropy to determine the weights of the criteria. PCA was used to reduce the criteria and the correlation between the criteria. Integration of PCA and DEA was used to evaluate suppliers. The performance of the model was compared with other methods and sensitivity analysis was performed. The ranking difference between the proposed method and other methods was analyzed. It was indicated that the proposed method has higher accuracy.

Lam et al. (2010) used a selection model based on PCA for the material SS problem. This was a method specially prepared for the target company. In the first step, the criterion selection was determined. In the second step, quantitative data on the criteria were collected. In the third step, the TFN was used to convert the judgment into quantitative data. In the fourth step, linear transformation methods were used to normalize supplier attributes using equations. In the fifth step, the criteria were reduced by applying PCA. This method can generate some values and they were mentioned in the study. One of the largest real estate companies in the People's Republic of China was used as an example. Finally, the Statistical Package for the Social Sciences (SPSS) software outputs of the proposed model were included in the study.

Forghani et al. (2018) worked to solve the SS problem in the pharmaceutical industry. They wanted to improve SS and reduce uncertainty. First, the PCA method was used to reduce the number of selection criteria determined. The criteria obtained from the PCA method were evaluated by decision-makers. With the Z-TOPSIS technique, the importance value of each supplier was obtained for each product. They used as input in Mixed Integer Linear Programming (MILP) to determine suppliers and product quantities and used Microsoft Excel to rank suppliers. It was observed that the method gave good results in the example of the pharmaceutical company.

Hatami-Marbini et al. (2020) presented an integrated method for SS. PCA and DEA methods were used. The gap in SCM literature for SS issues when data are interdependent was addressed. The agri-food industry was used as an example. This proposed method addressed the statistical limitations and challenges in SS. When the results of the organization's internal and external strategy were examined, it was concluded that the growth strategy is a strategic action.

Karami et al. (2021) developed a quantitative and qualitative decision-making framework to enable the logistician to systematically select suppliers. It consists of three steps. In the first stage, the criteria are reduced with PCA. In the second stage, efficient suppliers are determined through DEA. In the third stage, efficient suppliers are ranked with VIKOR. A study was conducted in a garment supply chain. As a result, it was found that the proposed method prevents incorrect estimates of supplier efficiency.

Jia et al. (2015) conducted a study to ensure sustainability in the fashion industry. They conducted research on choosing the most appropriate supplier to ensure sustainable material supply in the fashion industry. They evaluated potential suppliers by determining a total of 12 criteria and applied the TOPSIS method to find the best supplier. Fuzzy sets and fuzzy numbers were used for evaluation. They ranked suppliers using this method. They included a case study to ensure sustainability from different aspects. The criteria were evaluated thanks to a team. They presented a sensitivity analysis of the study. As a result, the harmony of the study was observed. They revealed that the study could be used to source materials to ensure sustainability in this sector. They suggested that it could also be used in different functions of the process.

Wang et al. (2020) applied several methods to procure materials by selecting the best supplier in the industry using different criteria. Vietnam was preferred for this study in the textile industry. They used a multi-criteria decision-making method to evaluate suppliers in the country. First, the criteria were determined, and the Analytic Network Process (ANP) model of Hybrid FST was used to determine the weight. PROMETHEE II, a multi-criteria decision-making method, was applied to rank the determined criteria. Thus, the best alternative was determined. PROMETHEE is an easy method to apply and gives better results. A case study is presented based on the Vietnamese industry. It was emphasized that the study can be used not only for SS in the textile industry but also for other different sectors.

Wang et al. (2020) used Supply Chain Operation Reference (SCOR), AHP, and DEA methods respectively to reach the best supplier in the oil industry. SCOR was implemented through a match to determine the criteria. Using expert opinions, the weight of each criterion was determined using AHP. The RIA model was used to rank potential suppliers. The results were examined, and it was decided that the most suitable suppliers were supplier 1, supplier 4, and supplier 10. It was also mentioned that the model will be beneficial for different industries and will contribute to SCM in the oil and gas industry.

Wang et al. (2018) applied a hybrid approach to accurately perform SS. This hybrid method is an MCDM method. SCOR metrics, AHP, and TOPSIS were applied respectively. The gas and oil industry were included as a case study. Following a comprehensive literature review, criteria were identified and defined. AHP was used to determine the weight of each criterion. The TOPSIS method was used to select the most suitable supplier. Based on the evaluation criteria, it was determined that the 5th supplier was the most appropriate supplier for the project. Visuals were used to evaluate the contribution of the criteria to the result obtained. Ranking values are presented in graphical form. The contribution of the study to the literature was to present a new hybrid MCDM model for SS. As a result, the method could be used both for the gas and oil industry and for other different sectors.

The studies on SS were evaluated and summarized information about the reviewed articles was given. A summary table was created for the articles included in the literature review and is shown in Table 2.1. The table includes information about the article name, year of publication, authors, and methods used in the study.

Table 2.1. Summary table for the articles exist in the literature review

Article Name	Publication Year	Authors	Methods
Application of PROMETHEE method for green supplier selection: a comparative result based on preference functions	2019	Abdullah, Chan, Afshari	PROMETHEE
Green supplier selection based on IFS and GRA	2013	Bali, Kose, Gumus	IFS GRA FST
A Methodology for Green Supplier Selection in Food Industries	2015	Banaeian, Mobli, Nielsen, Omid	Fuzzy and Gray Set Theories
An integrated weighting and ranking model based on entropy, DEA and PCA considering two aggregation approaches for resilient supplier selection problem	2020	Davoudabadi, Mousavi, Sharifi	PCA DEA
Structural equation modeling of E-supplier selection criteria in mechanical manufacturing industries	2021	Garg	SEM
A strategy-based framework for supplier selection: A grey PCA-DEA approach	2022	Hatami-Marbini, Hekmat, Agrell	PCA DEA
Supplier selection and evaluation in the garment supply chain: An integrated DEA–PCA–VIKOR approach	2021	Karami, Ghasemy Yaghin, Mousazadegan	DEA PCA VIKOR
Incorporating management opinion in green supplier selection model using quality function deployment and interactive fuzzy programming	2022	Khattak, Naseem, Ullah, Imran, El Ferik	Multi-objective Interactive Fuzzy Programming QFD
Developing a green supplier selection model by using the DANP with VIKOR	2015	Kuo, Hsu, Li	DEMATEL ANP VIKOR
A material supplier selection model for property developers using Fuzzy Principal Component Analysis	2010	Lam, Tao, Lam	PCA TFN SPSS
A green supplier selection model for high-tech industry	2009	Lee, Kang, Hsu, Hung	Fuzzy Extended AHP
Green supplier selection in straw biomass industry based on cloud model and possibility degree	2019	Lu, Sun, Wang, Xu	CM Fuzzy AHP

Table 2.1. Summary table for the articles exist in the literature review **(continued)**

Article Name	Publication Year	Authors	Methods
Strategic supplier selection for renewable energy supply chain under green capabilities (fuzzy BWM-WASPAS-COPRAS approach)	2022	Masoomi, Sahebi, Fathi, Yıldırım, Ghorbani	The fuzzy BWM COPRAS WASPAS
Green supplier selection for the steel industry using BWM and fuzzy TOPSIS: A case study of Khouzestan steel company	2020	Oroojeni Mohammad Javad, Darvishi, Oroojeni Mohammad Javad	BWM Fuzzy TOPSIS
A Hybrid MCDM Approach for Large Group Green Supplier Selection With Uncertain Linguistic Information	2018	Quan, Wang, Liu, Shi	Ant Colony Algorithm The Multi Objective Optimization
Sustainable supplier selection in the textile dyeing industry: An integrated multi-criteria decision analytics approach	2022	Rahman, Bari, Ali, Taghipour	SWARA PAS
Big data cloud computing framework for low carbon supplier selection in the beef supply chain	2018	Singh, Kumari, Malekpoor, Mishra	Fuzzy AHP DEMATEL Fuzzy TOPSIS
A Flexible Decision-Making Method for Green Supplier Selection Integrating TOPSIS and GRA Under the Single-Valued Neutrosophic Environment	2021	Sun, Cai	TOPSIS and GRA
Resilient supplier selection and segmentation in grey environment	2019	Valipour Parkouhi, Safaei Ghadikolaei, Fallah Lajimi	Grey DEMATEL Grey SAW
Integrated QFD-MCDM framework for green supplier selection	2017	Yazdani, Chatterjee, Zavadskas, Hashemkhani Zolfani	DEMATEL QFD COPRAS
Green supplier selection using topsis method: A case study from the automotive supply industry	2019	Yildiz	TOPSIS
Selecting Green Supplier of Thermal Power Equipment by Using a Hybrid MCDM Method for Sustainability	2014	Zhao, Guo	Fuzzy Entropy-TOPSIS
A supplier selection model in pharmaceutical supply chain using PCA, Z-TOPSIS and MILP: A case study	2018	Forghani, Sadjadi, Farhang Moghadam	PCA Z-TOPSIS MILP
Supplier Selection Problems in Fashion Business Operations with Sustainability Considerations	2015	Jia Govindan Choi Rajendran	TOPSIS

Table 2.1. Summary table for the articles exist in the literature review **(continued)**

Article Name	Publication Year	Authors	Methods
Multi-Criteria Decision Model for the Selection of Suppliers in the Textile Industry	2020	Wang Viet Ho Nguyen Nguyen	SCOR FAHP PROMETHEE II
Multi-Criteria Decision Making (MCDM) Model for Supplier Evaluation and Selection for Oil Production Projects in Vietnam	2020	Wang Tsai Ho Nguyen Huang	SCOR AHP DEA
A Multi-Criteria Decision-Making (MCDM) Approach Using Hybrid SCOR Metrics, AHP, and TOPSIS for Supplier Evaluation and Selection in the Gas and Oil Industry	2018	Wang Huang Cheng Nguyen	SCOR AHP TOPSIS

3. MATERIAL AND METHODS

3.1. Supplier Selection

SS is the process of identifying, and evaluating suppliers from which companies will supply products and contracting with them. The main objective of the SS process is to reduce purchasing risk, maximize total value for the buyer, and develop long-term relationships between buyer and supplier.

Selecting a supplier requires some steps to be followed. Starting from determining the requirements correctly, researching potential suppliers, researching the capabilities and capacities of potential suppliers, etc.

SS criteria are carried out by a team that has been established. Opinions and suggestions from different departments can be taken into consideration. SCM plays a role in purchasing department selection. Generally, the needs of the business in the fields of production, sales, and logistics are used. Potential suppliers are evaluated in detail. The degree of importance of the criteria can be determined using a scoring system or by employing different weighting methods. The criteria for a business can vary depending on the priorities, needs, and strategies

Some specific steps need to be followed for SS. It is possible to proceed more systematically by following these steps. SS process is as given in Figure 3.1.

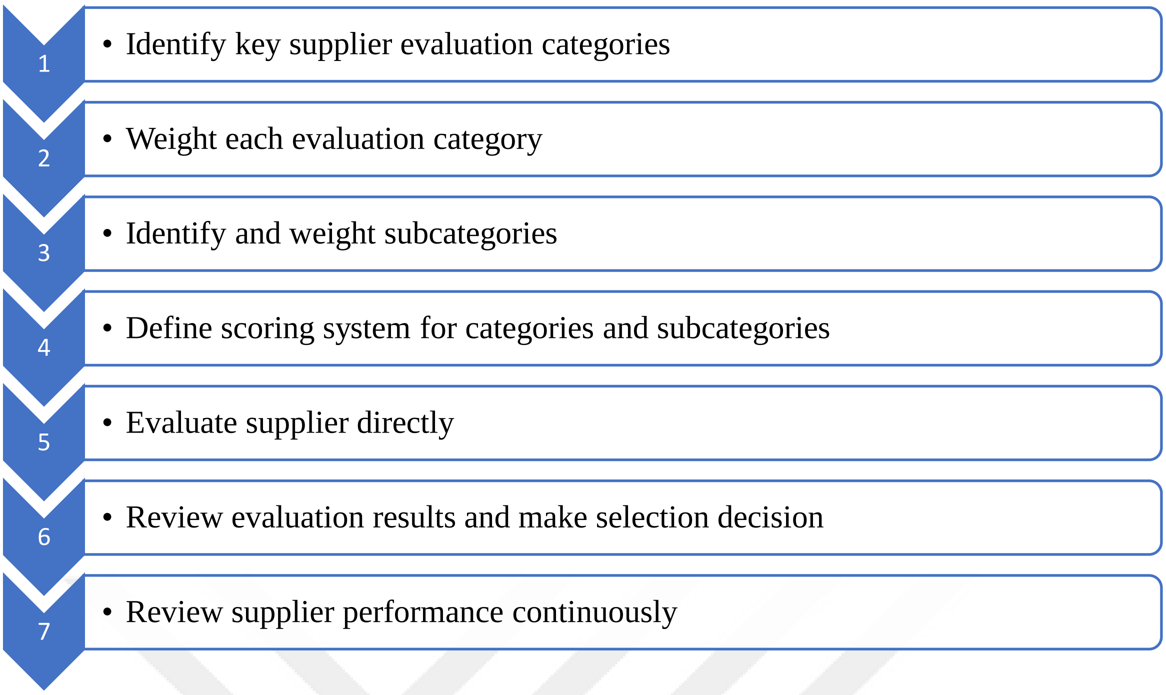

Figure 3.1. Supplier selection process

Choosing a suitable supplier can provide many benefits, increase the quality of product and service and productivity, minimize costs, increase profit, shorten product times, and increase client contentment. It can even help businesses adapt to changes in the market more easily, gain a flexible structure, and be competitive in the market. Choosing the right supplier is very important for a successful business strategy.

There are many techniques developed on this topic for SS. Such as Cost-based Models, MP Models, Statistical Models, AI Models, MCDM Models (Figure 3.2.). Hybrid models created by combining these methods are also used. The MCDM method is the most widely used method for SS. It evaluates many factors simultaneously, both quantitatively and qualitatively.

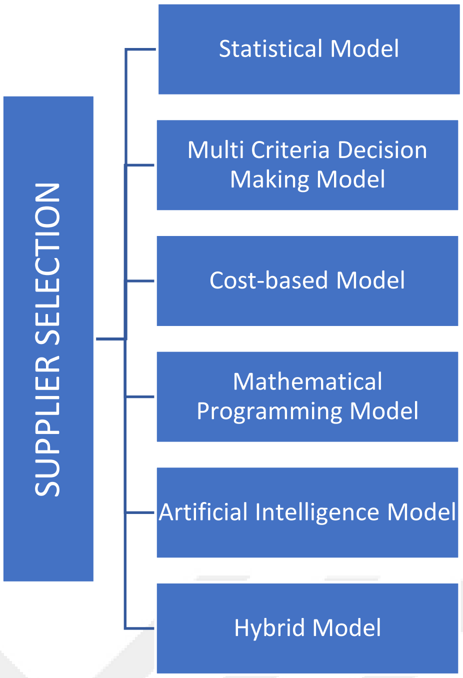

Figure 3.2. Supplier selection methods

MCDM is a sub-discipline of operations research that enables decision-making by evaluating more than one criterion. It is based on modeling the decision process according to criteria and maximizing the benefit to be obtained by the decision maker. Many quantitative and qualitative factors can be evaluated simultaneously. MCDM methods include the best possible solution that meets more than one criterion. There is no uniquely optimal solution for these methods, decision makers need to use their preferences to distinguish between solutions.

The MCDM method can be used in a decision-making process with many criteria. It can be applied with the help of mathematical models, techniques, and tools. Taking the right steps in the correct order makes achieving the desired outcome easier. The following steps can be followed: Criteria identification, weighting, listing alternatives, performance evaluation, decision analysis, and selecting the most appropriate alternative. When determining criteria, all criteria affecting the decision should be considered. The important ones should be identified and defined. When determining weights, the degree of importance of each criterion should be determined. Alternatives are options with different characteristics to choose from. Different methods and tools can be used in decision analysis. To determine the most appropriate option, a ranking, and a choice is made among the alternatives.

There are many factors to consider when choosing a supplier. Quality, reliability, cost, service, capacity, resources, price, and delivery time are just a few of them. Each business should determine its criteria following its own needs, expectations, and resources. Potential suppliers' past performance, references, reputation, and business ethics should be taken into consideration. After the SS process is completed, a contract is prepared and mutually signed within the scope of responsibilities, terms, and conditions. During the procurement process, the supplier is observed and evaluated, then improvements are made when necessary.

SS methods and criteria are important factors affecting a company's development and competitiveness. For many years, the most important selection criterion has been price. In addition to price, factors such as quality and cost have also been effective in selection. Recently, this traditional approach has started to change. In addition to quality, cost, and service, criteria have become more complex due to concerns such as the environment, social responsibility, and customer satisfaction. It has been realized that collaborating with the right suppliers can make a strategic difference. Managers who want to increase the strategic power of their companies and increase their competitiveness in the market have turned to improvement. Over time, these criteria have started to change to consider the demands and requests of customers and to respond quickly to customer demands.

Many sources (i.e., articles and theses) that may be suitable for the study were examined. The criteria included in the studies were reviewed. There may be many criteria that are important for making a choice. This varies according to the needs of the enterprises. Consequently, the literature search and the criteria used in SS methods are given as follows. It is divided into seven main headings. These are cost, delivery, quality, service, environmental, social, source, and capabilities. A large criteria table has been created and given in Table 3.1.

Table 3.1. Table of supplier selection criteria

CRITERIA						
COST	**DELIVERY**	**QUALITY**	**SERVICE**	**ENVIRONMENTAL**	**SOCIAL**	**SOURCE AND CAPABILITIES**
Cost	Delivery	Product features	Warranty policy	Green design	Interest of employee	Capability
Assets	Distance	Standards	After sales service quality	Green packaging	Desire for business	Sourcing
Transportation cost	Location	Quality	Service system	Reuse	Relationship	Availability of resources
Product price	Lead time	Production capacity	Ease of communication	Recycling	Communication skills	Sustainable raw materials
Payment options	Transport properties	Defect ratio	Responsiveness	Environmental control system	Training	Capability of produce
Discount	Carriers	Conformance to requirement	Quick responsive time	Environmental competencies	Company image	Technical capability
Material price	Just-in-Time	Country of origin	Repair services	Pollution control	Reputation	Ability to product change
Payment method		Continuous improvement	Monitoring	Consumption of energy	Impression	Sharing information
Financial position				ISO standards	Attitude	
Minimum order quantity				Environmental management system	Market recognition	
Internal cost				Quality of chemical	Respect for policy	
					Information disclosure	

The criteria, descriptions, and measures given in Table 3.2 are taken from the article (Karami, Yaghin, and Mousazadegan, 2021). As it is shown in the table, 10 criteria are employed in criteria reduction using the PCA method.

Table 3.2. Criteria used for PCA (Karami, Yaghin and Mousazadegan, 2021)

Number	Criteria	Description and Measures
1	Quality	Product damage at each a lot
2	Price	Toman
3	Location	Distance
4	Lead-time	Amount of time between ordering and receiving
5	Monetary position	Qualitative
6	Financial position	Qualitative
7	On-time delivery	Ratio of products delivered on time
8	Ability to product change	Product mix and providing a range of models
9	Service	The allowable period for product return
10	Capacity	Product availability

Table 3.3. Data of garment suppliers (Karami, Yaghin, and Mousazadegan, 2021)

Criteria / Suppliers	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
1	9	398	24	19	1	7	80	5	14	240
2	7	326	37	14	7	5	85	6	21	280
3	13	301	30	9	7	5	90	12	7	300
4	13	400	27	15	1	3	88	15	30	440
5	8	319	19	33	5	3	76	20	21	400
6	8	430	31	20	1	1	95	23	30	800
7	7	337	22	18	1	3	83	17	14	300
8	3	530	29	33	5	3	80	19	30	240
9	8	350	25	23	5	3	70	13	21	240
10	5	490	23	24	1	1	92	25	30	720
11	23	315	18	12	7	7	77	14	7	380
12	7	600	26	29	3	1	90	12	30	500

3.2. Principal Component Analysis

PCA is a method employed for dimensionality reduction in extensive datasets. This is accomplished by condensing numerous variables into a more concise set of variables. The aim is to analyze large data sets without losing information. PCA can be used in many areas such as recognition, classification, and image compression. The variation in the data is transformed into a new coordinate system containing fewer dimensions with the PCA method. PCA is used to reduce the number of variables to an independent set when they are related to each other. It is desired to destroy the addiction structure. It is used to understand the relationship between data and to visualize data. It helps us understand and analyze large-scale data.

The steps to be followed to apply the PCA method are given below:

1. Standardization: Variables are normalized to analyze the contribution of each variable to the analysis equally. The data must be evaluated on the same scale and have comparable variance. Therefore, it is important to normalize the data before PCA for the variances of the variables. The average value is calculated for each feature. The mean is subtracted from each variable and is divided by the standard deviation.

2. Calculating Covariance Matrix: The covariance matrix of the variables is calculated to see how the variables change with the calculated average value and whether there is a relationship between the variables, and to identify and separate variables that are highly related to each other. The matrix consists of the covariances linked to every conceivable pair of initial variables.

Standardized data are multiplied by their transpose. Diagonal entries represent the variances of each feature. Off-diagonal entries represent covariances between different features. By looking at the covariance matrix, it can be seen whether the features are positively or negatively related or how they change. This matrix is used for eigenvector and eigenvalue calculations.

3. Calculating Eigenvectors and Eigenvalues: Eigenvector and Eigenvalue are concepts calculated to determine the fundamental components of data. Eigenvectors are the directions in which the data changes the most, and eigenvalues are the amount of variation along those directions. Eigenvectors correspond to the largest variances in the data. Eigenvectors are the basic components of the data set. They are used to project the data into a lower dimensional space.

4. Identifying Principal Components: The principal components correspond to the largest eigenvalues. These explain the greatest variance in the data. The number of principal components depends on the percentage of variance the user wants to preserve. Low eigenvalues are selected and discarded. A matrix of vectors is created with the others.

5. Reflect Data into Main Components: A new array of axes is created for easier evaluation of the data. A new dataset with lower dimensions is created from the initial original data.

While the data is reflected in the main component, as much information as possible is tried to be preserved and the dimensionality of the data is reduced. As a result, a new lower-dimensional dataset is formed, called the transformed dataset, which still contains most of the information.

PCA is a multivariate statistical technique that creates new artificial variables based on interconnected data. By minimizing the reduction of information, it helps to decrease the correlation effects between the given criteria. It's important to reduce the number of criteria that need to be analyzed to streamline the decision-making process and save time.

By reducing the number of criteria included in the study, we can select with fewer criteria. That is why we use PCA, a powerful technique that allows us to identify the most important variables and exclude those that are less relevant. Thus, by identifying the similarities and differences in the data, the volume of complex criteria will be reduced without a loss of information and a more manageable set of criteria will be obtained.

3.3. Entropy Weighting Method

EWM is an information weighting method used in decision-making problems. With this method, the weights of different indexes are determined according to the degree of distribution. The smaller the entropy value, the greater the degree of dispersion of the index and the greater the weight it has.

It ensures that the computed weights are not influenced by human factors and yields more objective outcomes. Since it is based solely on objective results, it can guarantee fairness and impartiality, which is why it is one of the most popular methods. Criteria can be weighted with an objective approach by applying the steps given as follows.

1. Normalize the Decision Matrix: Data may be at different scales or ranges. This makes data processing difficult and may also affect reaching the correct result. To prevent this, normalizing the data before criteria weighting increases the accuracy score. Normalization assigns the data to a certain range and allows data to be examined within a certain range. Different calculations can be used for the normalization process. It is obtained by dividing the number by the sum of the numbers in its column in the following step:

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{3.1}$$

2. Calculate the entropy values for each criterion: When finding the entropy values of the data, the calculation is made based on the normalized values (p_{ij}). The entropy value is calculated for each column. The natural logarithm of each normal value is taken and multiplied by itself. By summing these values in the same column, the entropy value (e_j) is found.

$$e_j = -k \sum_{j=1}^{n} p_{ij} * \ln(p_{ij}) \tag{3.2}$$

3.Determine the weight values for each criterion: The entropy value must be subtracted from 1 to find the differentiation value of each number. The 1- e_j value in the numerator section of the formula can also be represented by the d_j value. Criteria are the differentiation value calculated for each column divided by the sum of the differentiation values.

$$w_j = \frac{1 - e_j}{\sum_{j=1}^{n}(1 - e_j)} \tag{3.3}$$

3.4. TOPSIS

TOPSIS is an MCDM in which the most accurate choice is made by evaluating and ranking alternatives under uncertainty according to criteria. The method was introduced in 1980. It is a widely used MCDM method. The TOPSIS method is related to the distance to the positive ideal solution. The method is applied by comparing a set of alternatives. Often the weights of the criteria are normalized because they are of incompatible dimensions. Alternatives are ranked using a general index according to their distance from ideal solutions. The positive ideal solution aims to maximize the benefits and minimize the cost. It consists of seven main steps:

1. Create an Evaluation Matrix: An evaluation matrix consisting of m alternatives and n criteria is created.

$$(x_{ij})m \times n \tag{3.4}$$

2. Normalization: The range of variables is standardized to analyze the contribution of each variable equally. It is easier to process data within a certain range. Most algorithms perform better when the features are at the same scale.

$$R=(r_{ij})m\times n \tag{3.5}$$

$$r_{ij} = \frac{x_{ij}}{\sqrt{\Sigma_{k=1}^{m} x_{k_j}^2}}, \qquad i = 1,2,\dots,m, \qquad j = 1,2,\cdots,n \tag{3.6}$$

3. Calculate Weight Normalized Decision Matrix: After assigning a weight to each value, they are normalized to sum to 1. Then, each normalized value is multiplied by its corresponding normalized weight.

$$t_{ij} = r_{ij} * w_{ij} \quad , \quad t = 1,2,\dots,m, \quad j = 1,2,\dots,n \tag{3.7}$$

4. Determine the best and the worst alternative for each criterion: The best and worst values of all alternatives are found.

$$A_w = \{\langle \max(t_{ij} | i = 1,2,\dots,m) \,|j \in J_-\rangle, \langle \min(t_{ij} | i = 1,2,\dots,m) \,|j \in J_+\rangle\} \equiv \{t_{wj} | j = 1,2,\dots,n\} \tag{3.8}$$

$$A_b = \{\langle \max(t_{ij} | i = 1,2,\dots,m) \,|j \in J_-\rangle, \langle \min(t_{ij} | i = 1,2,\dots,m) \,|j \in J_+\rangle\} \equiv \{t_{wj} | j = 1,2,\dots,n\} \tag{3.9}$$

5. Calculate the Euclidean distance between the target alternative and the best/worst alternative:

$$d_{iw} = \sqrt{\sum_{j=1}^{n}\left(t_{ij} - t_{wj}\right)^2}\ , \qquad i = 1, 2, \ldots, m \tag{3.10}$$

$$d_{ib} = \sqrt{\sum_{j=1}^{n}\left(t_{ij} - t_{bj}\right)^2}\ , \qquad i=1, 2, \ldots, m \tag{3.11}$$

6. Calculate the similarity to the worst condition: For each alternative, the similarity to the worst alternative is calculated.

$$s_{iw} = \frac{d_{iw}}{d_{iw}+d_{ib}}\ , \qquad 0 \leq s_{iw} \leq 1, \quad i=1, 2, \ldots, m \tag{3.12}$$

7. Rank the alternatives: All alternatives are ranked by scores. The best alternative gets the highest score. The best results are obtained according to the TOPSIS Method.

3.5. VIKOR

The VIKOR method is an MCDM method. It is used to find the best compromise solution between conflicting criteria. It is used for decision-making in many different fields such as engineering, management, and environmental sciences. It is carried out in seven steps.

1. Best and worst values are determined for each criterion in the decision matrix. It is calculated according to the objective function of each criterion. The worst value in each column is f_i^* and the worst value is f_i^-.

For max objective:

$$f_i^* = max_j f_{ij}\ , f_i^- = min_j f_{ij} \tag{3.13}$$

For min objective:

$$f_i^* = min_j f_{ij} , f_i^- = max_j f_{ij} \quad (3.14)$$

2.Normalization is applied to examine the criteria in the same and within a certain range. This ensures that all criteria are examined equally.

For max objective:

$$r_{ij} = x_{ij} - \frac{x_j^-}{x_j^* - x_j^-} \quad (3.15)$$

For min objective:

$$r_{ij} = \frac{x_j^* - x_{ij}}{x_j^* - x_j^-} \quad (3.16)$$

4. The normalized matrix is weighted. The V matrix is obtained by multiplying the criterion weight by each element in the decision matrix.

$$V_{ij} = r_{ij} * w_{K1} \quad (3.17)$$

5.S ratio is calculated. The S ratio shows how close each alternative is to the ideal solution. It is calculated using the distance to the ideal solution and the distance to the negative ideal solution. R value is calculated.

$$S_i = \sum_j^n w_j * \frac{f_j^* - x_{ij}}{f_j^* - f_j^-} \quad (3.18)$$

$$R_j = max_j \frac{w_j\left(f_j^* - x_{ij}\right)}{\left(f_j^* - f_j^-\right)} \quad (3.19)$$

6. The Q ratio is calculated for each alternative. It is measured by the average distance of each alternative from the ideal solution. It considers the best and worst Q ratios. The value of q represents the maximum group utility and (1-q) the minimum regret.

$$S^{*} = min\{S_i\}, S^{-} = \max\{S_i\}, R^{*} = max\{S_i\}, R^{-} = \min\{S_i\} \tag{3.20}$$

$$Q_i = q * \frac{S_i - S^{*}}{S^{-} - S^{*}} + (1 - q) * \frac{R_i - R^{*}}{R^{-} - R^{*}} \tag{3.21}$$

7. Alternatives are ranked according to their Q ratios. The most appropriate result is selected if the Q values satisfy the following 2 conditions. “m” is the number of alternatives.

Condition 1:

$$Q(A^2) - Q(A^1) \geq DQ\,, \quad DQ = \frac{1}{m - 1} \tag{3.22}$$

Condition 2: The alternative with the best Q value must have achieved the best result in at least one of the S_i or R_i values.

4. RESULTS AND DISCUSSION

4.1. Integrated PCA-Entropy Weighting Method-TOPSIS

As a result of the literature research, 10 specific criteria have been selected to aid the process of SS in the garment industry. (Karami, Yaghin and Mousazadegan, 2021). Twelve suppliers that supply products in the garment industry have been determined to be chosen from among them. It is decided to use the PCA method to reduce the number of interrelated variables that affect the choice of an independent set. To implement the method, the number of variables is reduced by using the Python 3.10 and SciKit Learn library.

In the program, code is created using sklearn.preprocessing and sklearn.decomposition libraries. MinMaxScalar is applied to the data and the normalization process is performed in the program used to keep the data in the range of 0-1. The min value is 0, the max value is 1 and, and the values are bound within this specified range. Normalization is the process of adjusting data values to a specific range, making it easier to examine and process data from different sources. This results in standardized data that is approximated to each other. Discrepancy normalization is a crucial step to ensure that data in different ranges are standardized and brought into the same range. This helps to avoid any misleading results and ensures that the study is accurate and reliable. It's really important to pay attention to this step to get meaningful insights from the data.PCA processed ten criteria and reduced them to six criteria as pc1, pc2, pc3, pc4, pc5, and pc6. With these principal components formed, the selection process continued. The new data table with six criteria values and twelve suppliers is as follows:

Table 4.1. Principal components that are acquired as a result of PCA

	pc1	**pc2**	**pc3**	**pc4**	**pc5**	**pc6**
1	0,50	-0,09	-0,19	0,80	0,12	-0,04
2	0,62	0,07	0,82	0,01	-0,15	0,10
3	0,93	-0,36	0,37	-0,26	-0,05	-0,28
4	-0,34	-0,37	0,03	0,23	0,002	0,33

Table 4.1. Principal components that are acquired as a result of PCA **(continued)**

	pca1	**pca2**	**pca3**	**pca4**	**pca5**	**pca6**
5	0,01	0,49	-0,48	-0,34	-0,17	0,005
6	-1,009	-0,56	0,14	-0,23	-0,11	0,06
7	0,05	-0,20	-0,40	0,27	-0,32	-0,21
8	-0,39	0,79	0,20	-0,01	0,07	-0,06
9	0,31	0,50	-0,12	0,005	-0,21	0,18
10	-1,09	-0,26	-0,19	-0,19	0,01	-0,08
11	1,19	-0,24	-0,40	-0,39	0,38	0,11
12	-0,79	0,24	0,22	0,10	0,43	-0,12

The EWM is used to determine the weights associated with the calculated PCA values. The weights are calculated for each value by using the entropy method and subsequently employed in the TOPSIS technique.

It is necessary to normalize the data to examine the program output data in a certain range and determine their weights. For this reason, excel software is used and the normalized data are given in Table 4.2. Each value is squared and the value in each column of the resulting matrix is summed. The data's square value is divided by the total sum of squares within its corresponding column, leading to the creation of a normalized decision matrix.

Table 4.2. Normalized data with EWM

	pc1	**pc2**	**pc3**	**pc4**	**pc5**	**pc6**
1	0,04	0,00	0,02	0,53	0,03	0,01
2	0,06	0,00	0,43	0,00	0,04	0,03
3	0,14	0,07	0,09	0,06	0,01	0,24
4	0,02	0,07	0,00	0,04	0,00	0,34
5	0,00	0,12	0,15	0,10	0,05	0,00
6	0,17	0,16	0,01	0,04	0,02	0,01

Table 4.2. Normalized data with EWM **(continued)**

	pc1	pc2	pc3	pc4	pc5	pc6
7	0,00	0,02	0,10	0,06	0,18	0,14
8	0,03	0,32	0,03	0,00	0,01	0,01
9	0,02	0,13	0,01	0,00	0,08	0,11
10	0,19	0,04	0,02	0,03	0,00	0,02
11	0,23	0,03	0,10	0,12	0,26	0,04
12	0,10	0,03	0,03	0,01	0,32	0,05

Each of the values in Table 4.2 is multiplied by itself and its natural logarithm. They are written in each cell of the matrix and the entropy values of the data are obtained.

Table 4.3. Multiplication of normalized data itself and its natural logarithm

	pc1	pc2	pc3	pc4	pc5	pc6
1	-0,13	-0,02	-0,09	-0,34	-0,10	-0,03
2	-0,17	-0,02	-0,36	0,00	-0,14	-0,11
3	-0,28	-0,18	-0,21	-0,17	-0,03	-0,34
4	-0,08	-0,19	-0,01	-0,14	0,00	-0,37
5	0,00	-0,26	-0,28	-0,23	-0,15	0,00
6	-0,30	-0,29	-0,06	-0,14	-0,09	-0,06
7	0,00	-0,08	-0,23	-0,17	-0,31	-0,27
8	-0,09	-0,36	-0,09	0,00	-0,04	-0,06
9	-0,07	-0,26	-0,04	0,00	-0,20	-0,24
10	-0,32	-0,12	-0,09	-0,10	0,00	-0,09
11	-0,34	-0,11	-0,23	-0,26	-0,35	-0,13
12	-0,23	-0,11	-0,11	-0,04	-0,37	-0,14

Table 4.4. Entropy values for each column (e_j) and differentiation value (d_j)

	pc1	**pc2**	**pc3**	**pc4**	**pc5**	**pc6**
$\mathbf{e_j}$	0,20	0,20	0,22	0,25	0,23	0,22
$\mathbf{d_j}$	0,80	0,80	0,78	0,75	0,77	0,78

The d_j values are obtained by subtracting the e_j values from 1. The weight values are calculated by dividing each d_j value by the total $d_j$value. The calculated weight values (w_j) are given in Table 4.5.

Table 4.5. Weight values obtained with EWM

	pc1	**pc2**	**pc3**	**pc4**	**pc5**	**pc6**
$\mathbf{w_j}$	0,17093	0,17086	0,16655	0,15942	0,16525	0,16699

The sum of calculated weights found by the entropy method is 1. The weight values are computed to assess their level of significance. The magnitudes of the criteria's weights are very close to each other.

The data obtained as a result of PCA are used in the TOPSIS method to select the most suitable supplier, taking into consideration their weights calculated by entropy. The TOPSIS method is implemented using the Excel software due to its user-friendly interface and widespread availability. It is aimed to take the closest distance to the positive ideal solution and the farthest distance to the negative ideal solution. The best possible solution is achieved by precisely balancing the distance between these two extremes.

The TOPSIS method is applied for twelve alternatives and six criteria using the weights calculated with the Entropy method. In the first step, an evaluation matrix (x_{ij}) is created. This particular matrix comprised of m criteria and n alternatives. Here, m corresponds to twelve alternatives and n corresponds to six criteria values.

In the second step, normalization is applied to the evaluation matrix. A new R matrix has been created. The R matrix is created by dividing the data itself by the square root of its square.

Table 4.6. R matrix for normalization

	pc1	pc2	pc3	pc4	pc5	pc6
1	0,20	-0,07	-0,16	0,73	0,17	-0,08
2	0,25	0,06	0,65	0,01	-0,21	0,18
3	0,37	-0,26	0,30	-0,24	-0,08	-0,49
4	-0,14	-0,27	0,03	0,21	0,00	0,59
5	0,01	0,35	-0,39	-0,31	-0,23	0,01
6	-0,41	-0,40	0,12	-0,21	-0,15	0,12
7	0,02	-0,15	-0,32	0,25	-0,42	-0,37
8	-0,16	0,57	0,16	-0,01	0,10	-0,12
9	0,13	0,36	-0,10	0,00	-0,28	0,32
10	-0,44	-0,19	-0,16	-0,17	0,03	-0,15
11	0,48	-0,17	-0,32	-0,35	0,51	0,20
12	-0,32	0,17	0,18	0,09	0,57	-0,21

Then, in the third step, the weighted normalized decision matrix (t_{ij}) is calculated. It is created by multiplying normalized data values by weight values calculated with entropy.

Table 4.7. Weighted normalized decision matrix (t_{ij})

	pc1	pc2	pc3	pc4	pc5	pc6
1	0,03	-0,01	-0,03	0,12	0,03	-0,01
2	0,04	0,01	0,11	0,00	-0,03	0,03
3	0,06	-0,04	0,05	-0,04	-0,01	-0,08
4	-0,02	-0,05	0,00	0,03	0,00	0,10
5	0,00	0,06	-0,06	-0,05	-0,04	0,00
6	-0,07	-0,07	0,02	-0,03	-0,02	0,02
7	0,00	-0,03	-0,05	0,04	-0,07	-0,06
8	-0,03	0,10	0,03	0,00	0,02	-0,02

Table 4.7. Weighted normalized decision matrix (t_{ij}) **(continued)**

	pc1	**pc2**	**pc3**	**pc4**	**pc5**	**pc6**
9	0,02	0,06	-0,02	0,00	-0,05	0,05
10	-0,08	-0,03	-0,03	-0,03	0,00	-0,03
11	0,08	-0,03	-0,05	-0,06	0,08	0,03
12	-0,05	0,03	0,03	0,01	0,09	-0,04

In the fourth step, the best and worst alternatives are determined. The best alternative, i.e. the (A_b) weighted normalized decision matrix is found by selecting the largest value in each column. The worst alternative, i.e. (A_w) is found by selecting the smallest value in each column of the weighted normalized decision matrix.

Table 4.8. The best and the worst alternative for each criterion

	pc1	**pc2**	**pc3**	**pc4**	**pc5**	**pc6**
$\mathbf{A_b}$	0,08	0,10	0,11	0,12	0,09	0,10
$\mathbf{A_w}$	-0,08	-0,07	-0,06	-0,06	-0,07	-0,08

In the fifth step, the distance between the best alternative and the worst alternative is found. This process is applied to all values in the column. The d_{iw} value is found by squaring the difference between the data and the worst alternative value, adding this value in each row, and taking the square root. The d_{ib} value is found by squaring the difference between the data and the best alternative value, adding this value in each row, and taking the square root. The values are listed in Table 4.9 given below.

In the sixth step, the similarity of each alternative to the worst case (s_{iw}) is calculated. The similarity value is calculated by dividing the worst value by the sum of the worst and best values.

In the last step, the SS is made. The s_{iw} values are calculated in the sixth step and the alternatives are ranked according to their scores. Among the six criteria, the best alternative is the value with the highest score. The ranking of 12 criteria is 2-1-12-8-4-9-3-6-7-11-10-5 in the hybrid PCA-EWM-TOPSIS method. When looking at the ranking, the second supplier with a maximum s_{iw} value of 0,71 is selected as the most suitable supplier, fifth supplier is the worst supplier with a value of 0,39 according to the study.

Table 4.9. Euclidean distance between the target alternative and the best/worst alternative, and ranking of the alternatives

	d_{ib}	d_{iw}	$d_{ib}+d_{iw}$	s_{iw}
1	0,22	0,49	0,71	0,69
2	0,21	0,51	0,72	0,71
3	0,30	0,39	0,70	0,57
4	0,24	0,45	0,69	0,65
5	0,30	0,19	0,50	0,39
6	0,32	0,34	0,66	0,52
7	0,32	0,34	0,67	0,51
8	0,23	0,43	0,66	0,65
9	0,24	0,39	0,62	0,62
10	0,32	0,28	0,60	0,46
11	0,28	0,27	0,55	0,50
12	0,24	0,45	0,69	0,65

4.2. Sensitivity Analysis for PCA-EWM-TOPSIS

Sensitivity analysis is conducted to observe the changes in the criteria included in the study depending on the weights. A series of new weight scenarios are created to interchange the criteria computed using the EWM method, followed by the reapplication of the TOPSIS method using the weight values under five distinct conditions. Scenario 1 is created by changing the weights of the first and sixth criteria, scenario 2 is created by changing the weights of the second and fifth criteria, and scenario 3 is created by changing the weights of the third and fourth criteria. Scenario 4 is created by changing the weights of the first and fourth criteria. Scenario 5 is created by changing the weights of the second and fourth criteria. The table of newly created ranking values is shown in Table 4.11. A line chart is created for these three scenarios. The created line graph is shown in Figure 4.1.

Table 4.10. Exchanged weight values for 5 different scenarios

	pca1	pca2	pca3	pca4	pca5	pca6
Scenario 1	0,1670	0,1709	0,1666	0,1594	0,1652	0,1709
Scenario 2	0,1709	0,1652	0,1666	0,1594	0,1709	0,1670
Scenario 3	0,1709	0,1709	0,1594	0,1666	0,1652	0,1670
Scenario 4	0,1594	0,1709	0,1666	0,1709	0,1652	0,1709
Scenario 5	0,1709	0,1594	0,1666	0,1709	0,1652	0,1670

The results of five different calculated scenarios are shown inTable 4.11. New ranking values s_{iw} calculated by the TOPSIS method are shown. In scenarios 1, scenarios 2, scenarios 4, and scenarios 5, the second supplier emerges as the top alternative based on the highest score, whereas in scenario 3, the ninth supplier achieves the highest score. While the values of the alternatives are very close to each other in the four scenarios, these values varied in scenario 3. Based on the assigned weights, the second supplier is recommended when considering scenario 1, scenario 2, scenario 4 and scenario 5, whereas selecting the ninth supplier is advised when considering scenario 3.

Table 4.11. Sensitivity analysis ranking values for three different scenarios

Supplier	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
1	0,52	0,53	0,54	0,53	0,54
2	**0,55**	**0,55**	0,50	**0,55**	**0,55**
3	0,38	0,39	0,59	0,37	0,39
4	0,49	0,49	0,67	0,50	0,50
5	0,36	0,36	0,58	0,36	0,35
6	0,31	0,31	0,55	0,31	0,31
7	0,29	0,29	0,53	0,29	0,30
8	0,50	0,49	0,69	0,50	0,49
9	0,49	0,48	**0,71**	0,49	0,48
10	0,26	0,26	0,53	0,26	0,25
11	0,48	0,48	0,63	0,46	0,47
12	0,49	0,49	0,65	0,49	0,49

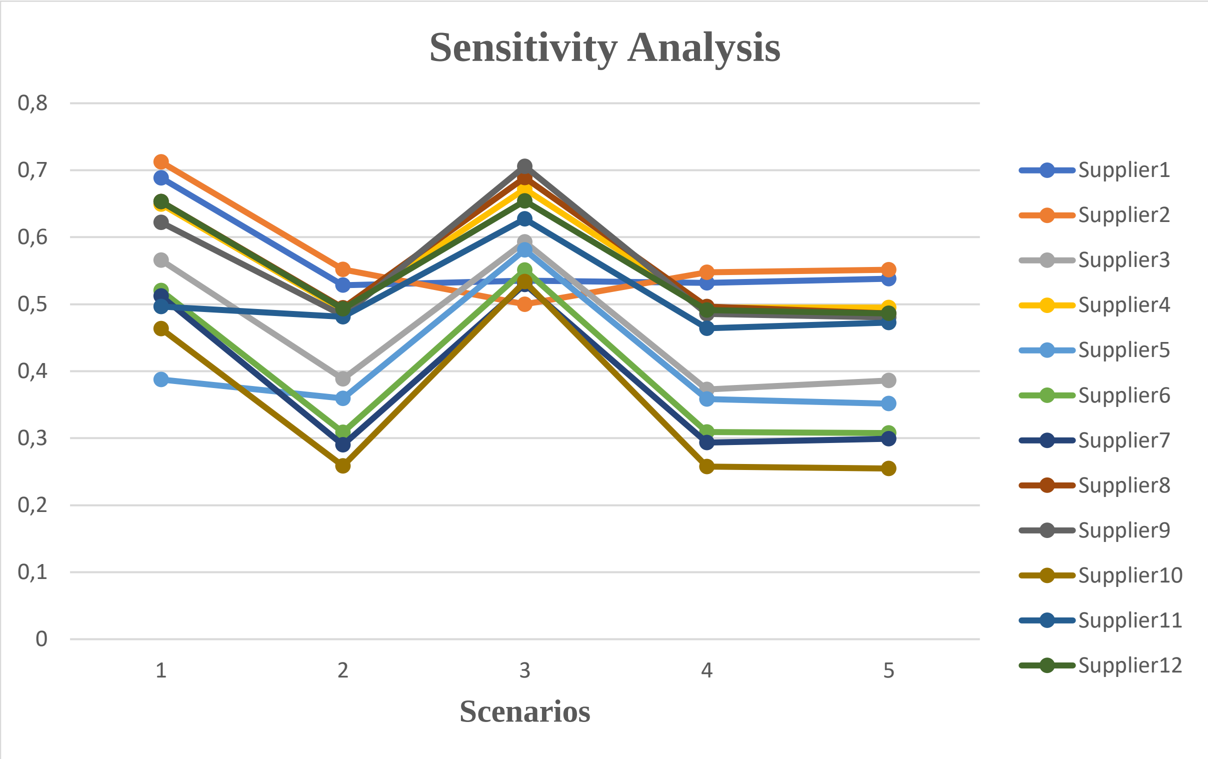

Figure 4.1. Line chart with sensitivity analysis results

A line chart is created to measure and visualize the sensitivity of the PCA-EWM-TOPSIS method. While there are five different scenarios on the horizontal axis of the line chart, the ranking values of 12 different criteria are included on the vertical axis. The TOPSIS technique is recalculated using the updated weight values listed in Table 4.10. In scenarios 1,2,4, and 5 it is seen that the second supplier obtained the highest value with a s_{iw} value of 0.55. In scenario 3, the ninth supplier has the highest value with a s_{iw}value of 0.71. Thus, when evaluating the dataset based on the criteria in scenario 3, the ninth alternative should be selected as the most suitable option. For the remaining cases, the ninth alternative should be selected as the most suitable alternative. Most of the alternatives have similar sensitivity to change. The alternative exhibiting lower sensitivity to alterations is the second alternative.

4.3. Entropy Weighting Method-TOPSIS

After applying the hybrid method, the EWM-TOPSIS method is used to compare the results obtained with and without criterion reduction using PCA. A flowchart showing the steps of EWM and TOPSIS and their interrelationship is shown in Figure 4.1. The output in EWM is the criteria weights, which are used to calculate the weighted normalized matrix in TOPSIS. To obtain the weighted normalized matrix, the R matrix values are multiplied by their respective criteria weights.

The decision matrix is contructed in EMW. Normalization of the decision matrix is constructed. Characteristic proportion is calculated. The entropy value is estimated and the entropy weight is computed. When calculating the weighted normalized matrix in the TOPSIS method, the R matrix values are multiplied by the calculated entropy weights.

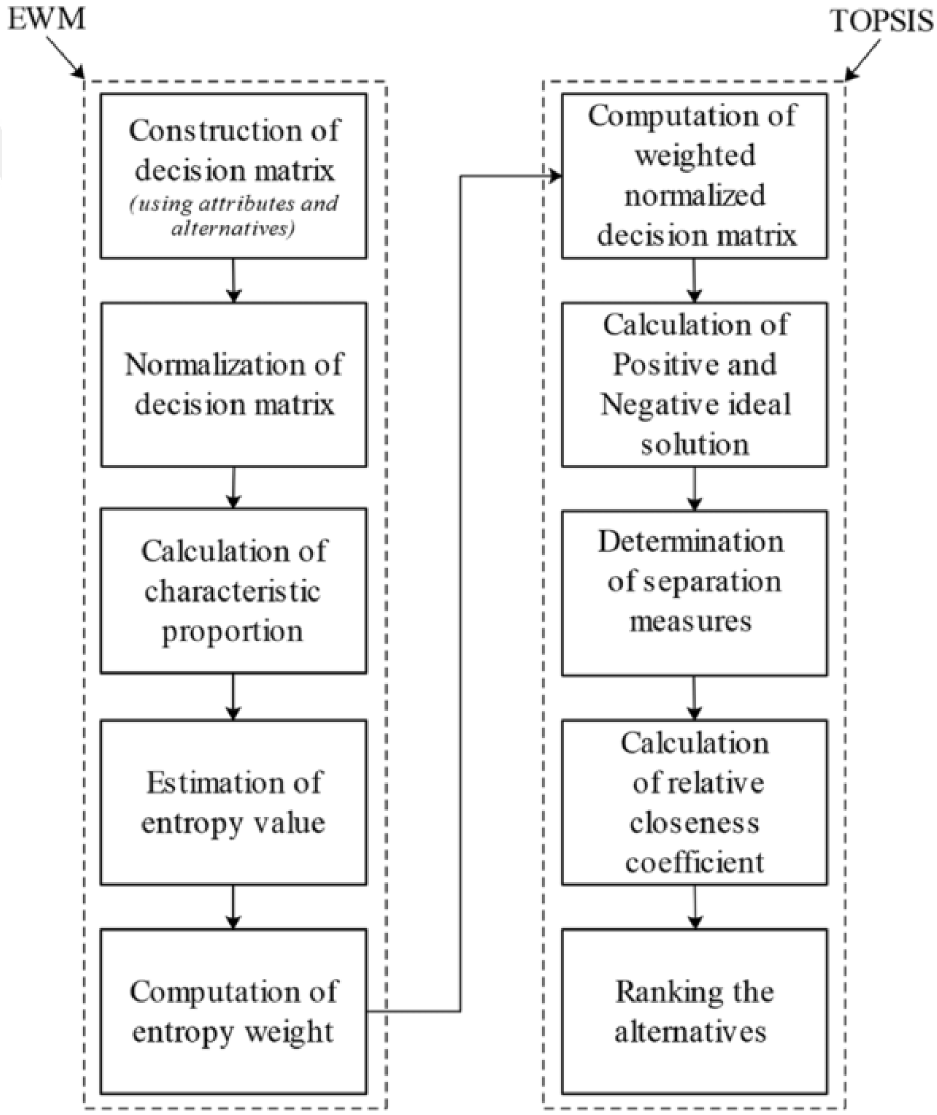

Figure 4.2. Flowchart showing EWM and TOPSIS steps respectively (Jain, Tomar and Jana, 2020)

The TOPSIS method is applied using ten criteria and twelve alternatives. The same steps are followed. The R matrix is created for normalization. A weighted normalized matrix is created. The weighted normalized matrix uses criteria weights calculated with EWM, which is also used in the hybrid method. These weights are displayed in Table 4.10. Among the criteria, on-time delivery (the seventh criterion) stands out with the highest weight, although the weights of all criteria are very close to each other.

Table 4.12. Weight values obtained for EWM-TOPSIS

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
W_{ij}	0,0992	0,1010	0,1011	0,1004	0,0980	0,0989	0,1013	0,1002	0,1001	0,0999

The R matrix is placed in Table 4.11. R matrix is created by dividing the data itself by the square root of its square. The weighted normalized decision matrix (t_{ij}) is obtained by multiplying the R matrix by the criteria weights. The weighted normalized decision matrix (t_{ij}) is located in Table 4.12.

Table 4.13. R matrix for normalization for EWM-TOPSIS

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
1	0,25	0,28	0,26	0,25	0,07	0,50	0,27	0,09	0,18	0,16
2	0,19	0,23	0,40	0,18	0,46	0,36	0,29	0,11	0,26	0,18
3	0,36	0,21	0,33	0,12	0,46	0,36	0,31	0,21	0,09	0,20
4	0,36	0,28	0,30	0,20	0,07	0,21	0,30	0,27	0,38	0,29
5	0,22	0,22	0,21	0,43	0,33	0,21	0,26	0,36	0,26	0,26
6	0,22	0,30	0,34	0,26	0,07	0,07	0,33	0,41	0,38	0,52
7	0,19	0,24	0,24	0,24	0,07	0,21	0,28	0,30	0,18	0,20
8	0,08	0,37	0,32	0,43	0,33	0,21	0,27	0,34	0,38	0,16
9	0,22	0,25	0,27	0,30	0,33	0,21	0,24	0,23	0,26	0,16
10	0,14	0,34	0,25	0,31	0,07	0,07	0,32	0,45	0,38	0,47
11	0,63	0,22	0,20	0,16	0,46	0,50	0,26	0,25	0,09	0,25
12	0,19	0,42	0,28	0,38	0,20	0,07	0,31	0,21	0,38	0,33

Table 4.14. Weighted normalized decision matrix (t_{ij}) for EWM-TOPSIS

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
1	0,02	0,03	0,03	0,02	0,01	0,05	0,03	0,01	0,02	0,16
2	0,02	0,02	0,04	0,02	0,04	0,04	0,03	0,01	0,03	0,18
3	0,04	0,02	0,03	0,01	0,04	0,04	0,03	0,02	0,01	0,20
4	0,04	0,03	0,03	0,02	0,01	0,02	0,03	0,03	0,04	0,29

Table 4.14. Weighted normalized decision matrix (t_{ij}) for EWM-TOPSIS **(continued)**

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
5	0,02	0,02	0,02	0,04	0,03	0,02	0,03	0,04	0,03	0,26
6	0,02	0,03	0,03	0,03	0,01	0,01	0,03	0,04	0,04	0,52
7	0,02	0,02	0,02	0,02	0,01	0,02	0,03	0,03	0,02	0,20
8	0,01	0,04	0,03	0,04	0,03	0,02	0,03	0,03	0,04	0,16
9	0,02	0,02	0,03	0,03	0,03	0,02	0,02	0,02	0,03	0,16
10	0,01	0,03	0,03	0,03	0,01	0,01	0,03	0,04	0,04	0,47
11	0,06	0,02	0,02	0,02	0,04	0,05	0,03	0,03	0,01	0,25
12	0,02	0,04	0,03	0,04	0,02	0,01	0,03	0,02	0,04	0,33

The best and worst alternative is determined by finding the minimum and maximum value in each column. The best alternative is the highest value of each criterion. The worst alternative is the lowest value of each criterion. The best and worst alternatives are shown in Table 4.13.

Table 4.15. The best and the worst alternative for each criterion for EWM-TOPSIS

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
A_b	0,06	0,04	0,04	0,04	0,04	0,05	0,03	0,04	0,04	0,52
A_w	0,01	0,02	0,02	0,01	0,01	0,01	0,02	0,01	0,01	0,16

Table 4.16. Euclidean distance between the target alternative and the best/worst alternative, and ranking of the alternatives for EWM-TOPSIS

	d_{ib}	d_{iw}	$d_{ib}+d_{iw}$	s_{iw}
1	0,37	0,05	0,42	0,12
2	0,35	0,06	0,41	0,15
3	0,33	0,07	0,40	0,17
4	0,24	0,14	0,38	0,36
5	0,27	0,12	0,39	0,31
6	0,07	0,37	0,44	0,83
7	0,34	0,05	0,39	0,13
8	0,37	0,06	0,43	0,14
9	0,37	0,04	0,42	0,11

Table 4.16. Euclidean distance between the target alternative and the best/worst alternative, and ranking of the alternatives for EWM-TOPSIS **(continued)**

	d_{ib}	d_{iw}	$d_{ib}+d_{iw}$	s_{iw}
10	0,09	0,32	0,41	0,77
11	0,28	0,12	0,40	0,30
12	0,21	0,18	0,39	0,46

The best and worst alternatives are calculated. Additionally, the distance between the best and worst alternatives is calculated. The similarity to the worst case is calculated and ranking is done according to the results obtained. The ranking is 6-10-12-4-5-11-3-2-8-7-1-9 in EWM-TOPSIS solved without PCA. The results show that the alternative with the highest value is the sixth alternative and the worst alternative is the ninth alternative. The results are included in Table 4.14.

4.4. EWM-VIKOR Method Results

The dataset employed in the PCA-EWM-TOPSIS approach is additionally solved by VIKOR and compared with the results of the PCA-EWM-TOPSIS method. While the second supplier is the best alternative in PCA-EWM-TOPSIS method, the seventh supplier is selected as the best alternative in VIKOR method. In light of the comprehensive analysis, it becomes evident that both the method employed and the assigned weights significantly influence the outcomes in SS problems.

Table 4.17. The data used for the VIKOR method, and best-worst values

Criteria / Suppliers	C_1 (max)	C_2 (min)	C_3 (min)	C_4 (min)	C_5 (max)	C_6 (max)	C_7 (max)	C_8 (max)	C_9 (max)	C_{10} (max)
1	9	398	24	19	1	7	80	5	14	240
2	7	326	37	14	7	5	85	6	21	280
3	13	301	30	9	7	5	90	12	7	300
4	13	400	27	15	1	3	88	15	30	440
5	8	319	19	33	5	3	76	20	21	400
6	8	430	31	20	1	1	95	23	30	800
7	7	337	22	18	1	3	83	17	14	300
8	3	530	29	33	5	3	80	19	30	240
9	8	350	25	23	5	3	70	13	21	240
10	5	490	23	24	1	1	92	25	30	720

Table 4.17. The data used for the VIKOR method, and best-worst values **(continued)**

Criteria / Suppliers	C_1 (max)	C_2 (min)	C_3 (min)	C_4 (min)	C_5 (max)	C_6 (max)	C_7 (max)	C_8 (max)	C_9 (max)	C_{10} (max)
11	23	315	18	12	7	7	77	14	7	380
12	7	600	26	29	3	1	90	12	30	500
Best Value (f_i^*)	23	301	18	9	7	7	95	25	30	800
Worst Value (f_i^-)	3	600	37	33	1	1	70	5	7	240

The objectives of the values in the decision matrix consisting of twelve alternatives and ten criteria are determined and shown in Table 4.12. They are written as min for the value to be minimized and max for the value to be maximized. The best and worst values within the dataset are identified. For the values to be minimized, the lowest value is the best value, while the highest value is the worst value. For the values to be maximized, the highest value is the best value, while the lowest value is the worst value. For example, C1 represents quality. Quality is a value that provides benefits for SCM. Therefore, quality is a value that should be maximized.

Table 4.18. Normalization matrix (R) for VIKOR method

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
1	0,30	0,32	0,32	0,42	0,00	1,00	0,40	0,00	0,30	0,00
2	0,20	0,08	1,00	0,21	1,00	0,67	0,60	0,05	0,61	0,07
3	0,50	0,00	0,63	0,00	1,00	0,67	0,80	0,35	0,00	0,11
4	0,50	0,33	0,47	0,25	0,00	0,33	0,72	0,50	1,00	0,36
5	0,25	0,06	0,05	1,00	0,67	0,33	0,24	0,75	0,61	0,29
6	0,25	0,43	0,68	0,46	0,00	0,00	1,00	0,90	1,00	1,00
7	0,20	0,12	0,21	0,38	0,00	0,33	0,52	0,60	0,30	0,11
8	0,00	0,77	0,58	1,00	0,67	0,33	0,40	0,70	1,00	0,00
9	0,25	0,16	0,37	0,58	0,67	0,33	0,00	0,40	0,61	0,00
10	0,10	0,63	0,26	0,63	0,00	0,00	0,88	1,00	1,00	0,86
11	1,00	0,05	0,00	0,13	1,00	1,00	0,28	0,45	0,00	0,25
12	0,20	1,00	0,42	0,83	0,33	0,00	0,80	0,35	1,00	0,46

In this step, the data needs to be normalized and the normalization matrix is created by calculating the min and max values in two different ways. For max objective, the worst value is subtracted from the number itself, divided by the value obtained by subtracting the worst value from the best value. For min objective, the number itself is subtracted from the best value, divided by the value obtained by subtracting the worst value from the best value. Thus, the R matrix is obtained.

Table 4.19. Weighted normalized matrix (V) for VIKOR method

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
1	0,03	0,03	0,03	0,04	0,00	0,10	0,05	0,00	0,03	0,00
2	0,02	0,01	0,10	0,02	0,10	0,07	0,07	0,01	0,06	0,01
3	0,05	0,00	0,06	0,00	0,10	0,07	0,09	0,04	0,00	0,01
4	0,05	0,03	0,05	0,03	0,00	0,03	0,08	0,05	0,10	0,04
5	0,02	0,01	0,01	0,10	0,07	0,03	0,03	0,08	0,06	0,03
6	0,02	0,04	0,07	0,05	0,00	0,00	0,12	0,09	0,10	0,10
7	0,02	0,01	0,02	0,04	0,00	0,03	0,06	0,06	0,03	0,01
8	0,00	0,08	0,06	0,10	0,07	0,03	0,05	0,07	0,10	0,00
9	0,02	0,02	0,04	0,06	0,07	0,03	0,00	0,04	0,06	0,00
10	0,01	0,06	0,03	0,06	0,00	0,00	0,10	0,10	0,10	0,09
11	0,10	0,00	0,00	0,01	0,10	0,10	0,03	0,05	0,00	0,02
12	0,02	0,10	0,04	0,08	0,03	0,00	0,09	0,04	0,10	0,05

The weighted normalized matrix is then calculated. The criteria weights are calculated with the EWM method as in other methods. Since the data used are the same, the VIKOR method is applied using the weight values in Table 4.10. The weighted normalized matrix is obtained by multiplying the normalized value by its weight and is showed in Table 4.14.

Table 4.20. Calculation of S_i, R_i and Q_i values for VIKOR method

Supplier	S_i	R_i	Q_i (q=0,50)
1	0,31	0,10	0,40
2	0,46	0,10	0,65
3	0,42	0,10	0,56
4	0,46	0,10	0,65
5	0,43	0,10	0,60
6	0,59	0,12	1,00
7	0,29	0,06	0,00
8	0,55	0,10	0,80
9	0,34	0,07	0,13
10	0,55	0,10	0,81
11	0,42	0,10	0,57
12	0,55	0,10	0,81
	Condition 1		0,13
	Condition 2		satisfied

Then, S_i and R_i values are calculated. In the weighted normalized decision matrix, the values in each row are summed and S_i values are obtained. R_i values are obtained by finding the max value in each row in the weighted normalized decision matrix. S^*, S^-, R^*, R^- values are calculated. Min S_i values give S^*, max S_i value gives S^-, min R_i value gives R^-, max R_i value gives R^*.

Q_i value is calculated for q=0,50 value. A computation is performed to assess the fulfillment of two distinct conditions. To determine Condition 1, the difference between the highest and second-highest values is calculated. This condition is satisfied if and only if the resulting difference is greater than or equal to a specific threshold value, DQ. The DQ value is found by dividing 1 by the number of alternatives minus 1. In the study, the second smallest value is 0.13 and the smallest value is 0. The difference is calculated as 0.13 and is equal to the DQ value. The DQ value is obtained by dividing the alternative number of 1 by 1 minus 11 and is 0.13. For Condition 2 to be met, the alternative with the best Q_i value must have achieved the best result in at least one of the S_i or R_i values. The lowest value of Si is 0.29. The lowest value of Ri is 0.06. The seventh alternative is the alternative with the lowest value of both. Although it is satisfactory for it to possess the minimum value in just one, it exhibits the minimum value in both instances. Considering both conditions according to the VIKOR method for the parameter value q=0.50, the seventh alternative that satisfies both conditions is determined as the most appropriate alternative. The worst alternative is the sixth alternative. The method differs significantly from the TOPSIS method due to their distinct focuses. TOPSIS focuses on the distance of alternatives from ideal solutions, while VIKOR aims at a compromise solution maximizing group utility and minimizing individual regret, leading to different outcomes (Uzun and Uzun Ozsahın, 2021).

5. CONCLUSION

The contribution of purchasing to the supply chain has increased considerably in recent years, and SS is one of the most critical steps in the supply chain (Ravindran and Warsing, 2013). It is a process that businesses attach importance to the correct and complete progress of production. To proceed correctly in this process, there are many different solutions for selecting the appropriate supplier. The focus in recent times has been on criteria to be considered within the sector, the degree of importance or weighting of these criteria, and the methodology for selecting suppliers to cooperate with.

MCDM is one of the most widely used methods in the past and today in selection problems. MCDM is a sub-discipline of operations research. It includes many different methods. This method, which is preferred in selection problems, aims to make a choice according to the effective criteria in the decision process and to maximize the benefit of the decision maker. The solution can be reached with different ways. In this study, TOPSIS and VIKOR, which are MCDM methods, are included.

This thesis presents a compelling analysis of SS, which is developed using data from a prominent garment company. The study employs 12 suppliers and incorporates 10 essential criteria outlined in the referenced article. By taking a comprehensive approach, this research provides valuable insights into the best practices and processes of the garment industry. The PCA method is intended to be used to decrease the dimensionality of large data set without loss of information. To choose the best supplier to purchase, it is necessary to choose among these 12 suppliers to find the most suitable supplier. Using PCA, six principal component values are obtained. The TOPSIS methodology has been introduced to identify the optimal supplier within the framework of this research. To achieve this objective, it is essential to ascertain the respective weights of the criteria that are employed. The determination of these weights is carried out through the utilization of the Entropy technique. Weight is given to each of the principal component values. Then, by using these weights TOPSIS method is applied, and a ranking is made at the end of the method. According to this ranking, it is determined that the second supplier is the best alternative with a maximum value of 0.71. The worst alternative is the fifth supplier with an s_{iw} value of 0.39. According to the results, the supplier with the maximum value is the second supplier and according to the study, the second supplier is selected as the most suitable supplier for this firm.

As the number of criteria and alternatives increases, the dependency between them increases and therefore the accuracy decreases when using the MCDM method. Therefore, since it is aimed to obtain more accurate results, different methods should be used to reduce dependency in such selection problems. One of these methods is the PCA. As seen in this study, applying PCA to complex data will be beneficial for the accuracy of the study. The selection process has been simplified by applying criteria reduction. The number of criteria has been reduced.

The hybrid method is also solved without applying criteria reduction. The EWM method is used to determine the criteria weights and the TOPSIS method is used for selection. The ranking results of the PCA-EWM-TOPSIS and EWM-TOPSIS methods are given. The results are compared. According to the computational results, for the PCA-EWM-TOPSIS, the best supplier is the second supplier, while supplier five is the worst alternative in the selection. For the EWM-TOPSIS, the best supplier is the sixth supplier (0,83) and the worst supplier (0,11) is the ninth supplier. The two results differ from each other. The proposed model is very useful for problems that have many criteria and alternatives (Sadatrasool, Bozorgi-Amiri and Yousefi-Babadi, 2016). As a result, it's possible for ranking results to differ. For a more comprehensive assessment of PCA's performance, it's recommended to compare its output using a larger dataset.

At the end of the hybrid PCA-EWM-TOPSIS method, a sensitivity analysis is performed. The results of the sensitivity analysis are presented in the form of tables and graphs. After interchanging the criterion weights and creating five different scenarios, it was observed that exchanging weights three and four produced a different result. The same result is observed even if the other different criteria weights are interchanged. The second alternative is less sensitive to change compared to other alternatives.

The VIKOR methodology is used to facilitate comparative analysis of outcomes using an alternative approach. Observations revealed distinctions between the outcomes obtained via the VIKOR method and those derived from the PCA-EWM-TOPSIS method. While the seventh supplier is selected as the most suitable alternative by the VIKOR method, the second supplier

is selected as the most suitable alternative by the PCA-EWM-TOPSIS method. Different results are obtained with different methods and different degrees of importance given to the criteria.
SS is an important element for companies to strengthen their competitive advantage and increase their operational efficiency. The factors that will influence SS for companies in the future will differ in terms of digitalization and sustainability. Global changes and collaborative relationships will come to the fore. To keep pace with changing trends, companies will aim to enhance their competitiveness while also making their supply chains more flexible, reliable, and efficient.

In today's rapidly changing business landscape, companies must be agile and competitive to stay ahead of the curve. To achieve this, they need to focus on building robust and flexible supply chains that can adapt quickly to changing market demands. By doing so, they can ensure that they stay ahead of the competition and provide their customers with the highest level of service possible.

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