VERİMLİLİK DERGİSİ

JOURNAL OF PRODUCTIVITY

T.C. SANAYİ VE TEKNOLOJİ BAKANLIĞI

#MİLLİ TEKNOLOJİ HAMLESİ

2025 | SPECIAL ISSUE OF PRODUCTIVITY FOR LOGISTICS

ISSN 1013-1388 | e-ISSN: 2757-6973

T.C. SANAYİ VE TEKNOLOJİ BAKANLIĞI

VERİMLİLİK DERGİSİ
Journal of Productivity

T.C. SANAYİ VE TEKNOLOJİ BAKANLIĞI

Stratejik Araştırmalar ve Verimlilik Genel Müdürlüğü'nün Yayınıdır

ISSN: 1013-1388 e-ISSN: 2757-6973

YIL: 2025 Sayı: Özel Sayı

Yayın Türü
Yerel-Süreli / Türkçe-İngilizce

Sahibi
T.C. SANAYİ VE TEKNOLOJİ BAKANLIĞI
STRATEJİK ARAŞTIRMALAR VE VERİMLİLİK GENEL MÜDÜRLÜĞÜ
adına
Genel Müdür
Abdullah BAŞAR

Editörler
Doç. Dr. Önder BELGİN
Dr. Kağan KARADEMİR

Sorumlu Yazı İşleri Müdürü
Doç. Dr. Önder BELGİN

Grafik Tasarım ve Uygulama
Fulya KOÇ

Dil Editörleri
Aytunç AYHAN
Şirin Müge KAVUNCU

Yönetim Yeri
T.C. SANAYİ VE TEKNOLOJİ BAKANLIĞI
STRATEJİK ARAŞTIRMALAR VE VERİMLİLİK GENEL MÜDÜRLÜĞÜ
Adres: Mustafa Kemal Mahallesi Dumlupınar Bulvarı
(Eskişehir Yolu 7. Km) 2151. Cadde No: 154/A
Çankaya 06510 ANKARA
Tel: 0 312 201 65 02
verimlilikdergisi@sanayi.gov.tr
https://dergipark.org.tr/tr/pub/verimlilik

Baskı Yeri
Elma Teknik Basım Matbaacılık
Adres: İvedik OSB Matbaacılar Sitesi 1516/1 Sk. No: 35
Yenimahalle 06378 ANKARA
Tel: 0 312 229 92 65 - Fax: 0 312 231 67 06 elma@elmateknikbasim.com.tr

Baskı Tarihi
03.02.2025

Verimlilik Dergisi'nde yayımlanan yazılarda belirtilen görüşler yazarlarına aittir. Dergide yayımlanan yazılardan, Verimlilik Dergisi'nin adı ve sayısı anılarak alıntı yapılabilir.

Verimlilikle ilgili tüm disiplinlerden gelecek makalelere açık olan *Verimlilik Dergisi,* 2004 yılından itibaren **"Hakemli Dergi"** statüsü ile yayımlanmaya başlamıştır. ***Verimlilik Dergisi,* 2008 yılından bu yana TÜBİTAK TR Dizin Sosyal ve Beşeri Bilimler Veri Tabanı'nda taranmaktadır.** *Verimlilik Dergisi*'nde yayınlanması istenen çalışmalara ilişkin süreç yönetimi, TÜBİTAK ULAKBİM DergiPark aracılığıyla yürütülmektedir.

İÇİNDEKİLER

CONTENTS

VERİMLİLİK DERGİSİ
JOURNAL OF PRODUCTIVITY

How Criteria Weights Influence Performance in Evaluating Logistic Productivity: An Application in the Emerging Markets Logistics Index

Elif Bulut[1], Seda Abacıoğlu[2]

ABSTRACT
Purpose: The differences between the criteria affecting the logistics performance of countries and their importance levels are meaningful in terms of policy development processes. It has been determined that the criteria are weighted equally in the emerging markets logistics index. For this reason, the study reweighted the criteria of the Emerging Markets Logistics Index and investigated the effects of weighting on the ranking. In this respect, the study aims to make the index more objective.
Methodology: In the study, Multi-Criteria Decision Making methods were utilized. Within this context, MEREC (Method Based on the Removal Effects of Criteria) was used to determine the criteria weights, while MABAC (Multi Attributive Border Approximation Area Comparison) and MAIRCA (Multi Attributive Ideal Real Comparative Analysis) methods were preferred to rank the alternatives.
Findings: In the study, it was concluded that the weighted values of the criteria are more consistent with the literature. Additionally, the new weights obtained have an effect on the ranking values of the countries.
Orginality: It is important that emerging markets provide an opportunity to develop infrastructure to increase logistics productivity and provide a platform for the implementation of new technologies in logistics operations. Furthermore, these markets enable the diversification and development of logistics services through the expanding consumer demand. This study differs from other studies in the literature because it preferred the Agility Emerging Markets Logistics Index (AEMLI) instead of the Logistic Performance Index (LPI) and used MEREC-based MABAC-MAIRCA methods.
Keywords*:* Logistic Productivity, AEMLI, MEREC, MABAC, MAIRCA.
JEL Codes: C40, F14, L90.

Lojistik Verimliliğini Değerlendirmede Kriter Ağırlıkları Performansı Nasıl Etkiliyor: Yeni Gelişen Pazarlar Lojistik Endeksinde Bir Uygulama

ÖZET
Amaç: Ülkelerin lojistik performanslarını etkileyen kriterler arasındaki farklılıklar ve önem dereceleri politika geliştirme süreçleri açısından anlam ifade etmektedir. Yeni gelişen pazarlar lojistik endeksinde kriterlere eşit düzeyde ağırlık verildiği tespit edilmiştir. Bu nedenle çalışmada Yeni Gelişen Pazarlar Lojistik Endeksi'ne ait kriterler yeniden ağırlıklandırılarak, ağırlıklandırmanın sıralamaya olan etkileri araştırılmıştır. Bu yönüyle çalışma incelemeye aldığı endeksi daha objektif hale getirmeyi amaçlamaktadır.
Yöntem: Çalışmada ÇKKV yöntemlerinden faydalanılmıştır. Bu çalışmada kriter ağırlıklarının belirlenmesinde MEREC, alternatiflerin sıralanmasında ise MABAC ve MAIRCA yöntemleri tercih edilmiştir.
Bulgular: Çalışmada kriterlerin ağırlıklandırılmış değerlerinin literatür ile daha uyumlu olduğu sonucuna ulaşılmıştır. Ayrıca elde edilen yeni ağırlıkların ise ülkelerin sıra değerleri üzerinde etkisi olduğu görülmüştür.
Özgünlük: Yeni gelişen pazarlar, lojistik verimliliği artırmak için altyapı geliştirme ve yeni teknolojilerin uygulanmasına zemin sağlamaktadır. Ayrıca, genişleyen tüketici talebi ile lojistik hizmetlerin çeşitlenmesine ve gelişmesine olanak tanımaktadır. Bu çalışma, Logistic Performance Index (LPI) yerine Agility Emerging Markets Logistics Index (AEMLI)'yi tercih etmesi ve MEREC tabanlı MABAC-MAIRCA yöntemlerini kullanmasıyla literatürdeki diğer çalışmalardan ayrılmaktadır.
Anahtar Kelimeler*:* Lojistik verimliliği, AEMLI, MEREC, MABAC, MAIRCA.
JEL Kodları: C40, F14, L90.

[1] Ondokuz Mayıs University, Faculty of Economics and Administrative Sciences, Department of Business Administration, Samsun, Türkiye.
[2] Ondokuz Mayıs University, Faculty of Economics and Administrative Sciences, Department of Business Administration, Samsun, Türkiye.

Corresponding Author: Elif Bulut, elif@omu.edu.tr
DOI: 10.51551/verimlilik.1518693
Research Article | Submitted: 19.07.2024 | Accepted: 23.10.2024
Cite: Bulut, E. and Abacıoğlu, S. (2025). "How Criteria Weights Influence Performance in Evaluating Logistic Productivity: An Application in the Emerging Markets Logistics Index", *Verimlilik Dergisi,* Productivity for Logistics (SI), 1-28.

1. INTRODUCTION

In contemporary contexts, logistics activities are crucial not only in the realms of production, exportation, sales, and post-sales processes but also in creating value that aligns with meeting customer expectations. This capability is essential for sustaining competitiveness for both enterprises and nations. The increasing significance attributed to logistics correlates with its expanding role in international commercial relations over successive periods. This correlation directs attention to logistics as a discipline predisposed towards fostering better collaboration among stakeholders located in diverse environments, enabling them to achieve mutual understanding and effective cooperation (Kuković, 2014). The increased prominence of transportation costs within total expenditures has underscored efforts to achieve superior operational outcomes at reduced costs, thereby highlighting the critical importance of controlling transportation, storage, and distribution activities (Bayraktutan and Özbilgin, 2015). The term “logistics”, derived from the Greek “logistikos” (pertaining to calculation) and the French “logistique” (pertaining to supply and lodgings), primarily originates from the fusion of “logic” and “statistics” (Gülenç and Karagöz, 2008). Logistics encompasses the entirety of activities aiding the management of product, information, and cash flows from production to consumption points (Lambert et al., 1998: 13-14). Initially confined to transportation and storage, logistics has evolved to encompass demand forecasting, inventory management, transportation, material handling, packaging, site selection, and order processing activities due to globalization and technological advancements. The importance of foreign trade, particularly in exports, is significant in enhancing countries' economic growth rates and enabling them to capture a larger share of international markets. Moreover, recent trends show that foreign trade transactions, which have increasingly become complex, now operate in conjunction with logistics. This has necessitated the imperative for countries to develop and integrate their logistics policies with their foreign trade strategies (Erkan, 2014).

The relationship between logistics performance and economic growth is becoming increasingly significant due to efficient logistics systems that facilitate trade, reduce costs, and enhance market access. Technological innovations, particularly automation and data analytics, contribute to making logistics processes more efficient, resulting in faster delivery times and lower supply chain costs. This can be considered a direct contributing factor to economic growth. In this context, investments in logistics infrastructure are said to support economic development by enhancing competitiveness. Emphasize the role of supply chains as a critical component of international trade, which includes elements such as freight transportation, warehousing, customs procedures, payment systems, and processes outsourced by manufacturers and sellers (Arvis et al., 2018: 8; Popescu and Sipos, 2014). Efficient logistics are vital for economic growth, diversification, and poverty alleviation. The logistics sector has accelerated the pace of economic globalization, enhancing inter-industry connections and intensifying the spread of growth stimuli across economic areas and on a global scale. Additionally, logistic development strengthens regional information and economic factor exchanges, expanding the market space, which in turn has a spillover effect on the economic growth of surrounding areas (Candemir and Çelebi, 2017; Khadim et al., 2021; Xu and Wang, 2017). The literature indicates that countries with better logistics infrastructure are more likely to experience high economic growth compared to those with weaker logistics infrastructure (Shikur, 2022). Numerous studies in the literature have examined the impact of logistics performance on economic development (Cheng and Peng, 2006; Chu, 2012; Hayaloğlu, 2015; Lean et al., 2014; Shikur, 2022). However, there are studies among these that have not achieved the expected results regarding the impact of logistics performance on economic development (Demurger, 2001; Pradhan and Bagchi, 2013). This raises the important question of what the sources of this discrepancy are. It is anticipated that quantitative values or numerical methods have an influence on these results. Tomassian et al. (2014) attempted to explain how a country’s likelihood of development is affected while considering general logistics variables along with some traditional explanatory variables. The authors concluded that there is a positive effect between logistics performance and a country’s likelihood of development. When searching for answers to the question of how quantitative values or numerical methods create differences, the following responses can be reached: the use of different measurement methods for distinct definitions (Khan et al., 2019), variations in the geography of the studies and the economic contexts related to this geography, and the improper use of numerical methods. For these reasons, there is a need for more consistent and robust methodological approaches to understand the relationship between logistics performance and economic growth. Sufficient data quality and the appropriate application of numerical methods can elucidate this relationship more accurately.

In this context, factors influencing the evolution of the concept of logistics include globalization, the emergence of new economic paradigms, differentiation in competition and its consequences, and technological advancements (Bakan and Şekkeli, 2017: 7). One of the indices used to determine the logistics performance of countries is the Agility Emerging Markets Logistics Index (AEMLI). AEMLI published by Agility, is a global study aimed at measuring the attractiveness of logistics investments in selected developing countries' markets (Bayraktutan and Özbilgin, 2015). In an index comprising specific categories, each category includes varying numbers of sub-variables. Statistical techniques are employed to calculate sub-indices, where the total index value is determined by averaging the values of these sub-indices. This scenario was exemplified in the 2023 publication of the index as follows: logistics capabilities within developing markets were measured using metrics for domestic opportunities, international opportunities, business fundamental, and digital readiness.

Technological advancements and trade liberalization offer new opportunities for countries to benefit from global markets in terms of growth and poverty reduction according to their own interests. Consequently, the cost of countries with weak connections to the global logistics network staying outside this network is increasing (Kara et al., 2009). This situation associated with domestic opportunities is significant for assessing logistics productivity and performance. Efficient utilization of infrastructure tailored to the needs of the logistics sector is considered a key element among logistics centers (Bamyacı, 2008: 68). Domestic opportunities measure the potential of domestic logistics services in emerging markets to meet domestic market demands. In addressing the information needs of foreign trade stakeholders regarding countries' logistics capacities and performances, domestic opportunities are recognized as an important factor (Kara, 2022). International opportunities are crucial in both exploring and creating prospects, referencing the vital importance of business connections for logistics (Galan and Torsein, 2021). Logistics productivity reveals how effectively supply chain companies are connected with both domestic and international opportunities (The World Bank, 2018: 7; Śtimac et al., 2021). From a business readiness perspective, the concept of logistics encompasses the analysis and determination of solutions for issues concerning business processes, costs, and services. In this context, logistics also facilitates the formation of departments and inter-company relationships within logistics enterprises (Pfohl, 2022: 45). Savytska et al. (2022) argue that in the context of digital readiness, business readiness forms the foundation for considering sector-specific factors. There is consensus in the literature that businesses are compelled and challenged to innovate in various departments of their operations due to Industry 4.0 (Chen, 2020; Khanzode et al., 2021; Masood and Sonntag, 2020; Somohano-Rodrîguez et al., 2022). It is emphasized that businesses require sufficient resources, capabilities, and strategies to possess the necessary resources for innovation. However, it has also been identified that businesses struggle to renew their processes and operations due to customer demands. Therefore, businesses collaborate with suppliers and customers in their supply chains in areas where they are lacking (Lassnig et al., 2022). Globalization and innovation management highlight the increasing importance of digital readiness for logistics productivity. The four headings described above correspond to the variables used by Agility in the AEMLI measurement from 2021 onwards. In this context, the alignment of selected variables with the literature is seen as an advantage of index calculation. Additionally, the index considers urbanization, wealth distribution, industry clustering, and market size in domestic logistics opportunities; density, customs, border, maritime, and airway efficiency in international logistics opportunities; market access, security, stability, and infrastructure in business readiness; and sustainability, skills, diversity, and development in digital transformation (Agility 2024: 62-63), which are cited as other advantages. In this context, it is stated that the index is theoretically sufficient and meets expectations. The index consists of a specific number of categories, with each category containing different numbers of sub-variables. Statistical techniques are used to calculate sub-indices, and the total index value is derived from the average of these sub-index values. This situation was exemplified in the 2023 publication of the index as follows: emerging fifty markets are measured by domestic opportunities, international opportunities, business fundamental, and digital readiness metrics, each assumed to have a 25% impact (Agility, 2022; Agility, 2023: 65). Therefore, our criticism is directed towards AEMLI allocating an equal and fixed 25% influence to each variable in the index.

In Multi-Criteria Decision Making (MCDM) methods, the stage of weighting criteria significantly influences the final decision-making process (Demir and Bircan, 2020). The accuracy of decision-making processes hinges on weighting methods that accurately determine the relative importance of each criterion (Singh and Pant, 2021). In this regard, the advantages of criterion weighting include establishing priorities, promoting higher-quality decision-making, effectively utilizing limited information presented in decision matrices, and guiding decision-making units towards sound decisions. In this context, the study suggests an alternative approach to ranking AEMLI by emphasizing the importance of weighting categories due to the utilization of MCDM methods in AEMLI index calculation. This approach aims to provide an alternative ranking to AEMLI by ensuring the proper weighting of categories.

This study aims to uncover the relationship between logistics performance and productivity through analyses that consider criterion weighting. It is observed that the significant growth of the global logistics industry has made logistics a crucial sector of the commercial economic system and a vital global economic activity in recent years. Logistics activities have an accelerating impact on the economy and productivity. Efficient logistics also play a crucial role in terms of a country's competitiveness and as a source of employment (Wong and Tang, 2018). Stock management, transportation and shipping, network and process management are considered among the primary operational efficiency factors within the concept of logistics. Evaluating logistics for productivity requires a broader assessment beyond conventional input-output concepts due to the nature of logistics. In this context, indicator and representational approaches are considered more appropriate for productivity measurements in logistics (Stainer, 1997). Today, manufacturing requires more intensive interactions to coordinate the production and distribution of numerous parts and components. It is noted that compared to the transportation networks of final goods, the networks of intermediate goods are complex and open to development. Consequently, logistics productivity is identified as a fundamental factor that needs to be analyzed when considering regional economic performance (Barilla et al., 2020). Therefore, in this study, 15 countries ranked in AEMLI are weighted and ranked using MEREC, MABAC, and MAIRCA methods based on variables determined by AEMLI. The study distinguishes itself from existing literature by aiming to contribute to the field through its findings rather than its approach to the topic. In line with this objective, the organization of the study includes a literature review that categorizes studies into three main areas: those examining logistics productivity, studies utilizing MCDM methods in logistics calculations, and studies integrating the MEREC, MABAC, or MAIRCA methods comprehensively. In addition to the introductory information provided in the study's structure, these categories are intended to enrich the literature with valuable insights. Under the methods section, explanatory details and notational representations of the numerical methods applied in the study are provided. The findings section presents numerical results obtained from the application of these methods in tabular format. In the conclusion section of the study, the findings are critically evaluated, conclusions are drawn, and implications for future research are discussed. Additionally, the expansions of all the abbreviations used in the text of this study are provided in the appendix section.

2. LITERATURE REVIEW

When considering the multidimensional impact of globalization, it is observed that the maturity of the historical background of the logistics concept aligns with its widespread presence in the literature on logistics studies. Furthermore, methods based on MCDM are increasingly utilized in the literature for conducting performance measurement and determining ranking values. Taking both aspects into account, the chronological presentation of the literature related to logistics productivity is provided. Studies that utilize MCDM methods for logistics performance measurement, integrating methods such as MEREC, MABAC, or MAIRCA, are summarized through tabular representation.

Xu et al. (2012) evaluate logistics management as a critical factor determining the successful delivery of a construction project. They investigate the loss of logistics productivity on construction sites through simulation applications, arguing that delays due to logistics activities can be better predicted. The study concludes that fluctuations in both logistics and construction activities significantly impact efficiency losses in logistics. Ohh (2012) focused on logistics productivity within the storage industry. The author employed Data Envelopment Analysis in their study. The research is significant in evaluating factors that determine efficiency in the logistics sector. The study concludes that the global number of warehouses and employees are important input criteria. Liang et al. (2020) evaluated the green total factor productivity of the logistics sector in their study. The authors suggested that governments and businesses should pay attention to the green and efficient development of the logistics sector. In Fan's (2019) study, the author utilized Data Envelopment Analysis method and the Luenberger Index to determine logistics productivity specifically within China. The study found that logistics productivities across Chinese regions are uneven, but policies implemented focus on addressing these disparities. Sereda (2021) emphasized that the digitalization of logistics processes is an effective factor in enhancing logistics productivity. The author concluded that digitalization is crucial for mitigating potential negative outcomes arising from the implementation of new technologies in logistics. Kalischuk and Nebelyuk (2021) focused on ensuring the efficiency of logistics business processes in supply chains. The authors aimed to identify logistics business processes in economic systems and concluded that the quality cycle, supply, and implementation stages are crucial. Rostek (2022) investigated the logistics productivity of a manufacturing firm. The study utilized econometric analysis as its methodology. The author proposes a productivity research procedure for the firm under study. Pfohl (2023) asserted that a prerequisite for success in logistics is the positive contribution of logistics services to the value creation of a company or an entire supply chain. A review of the literature on logistics productivity reveals that determining factors vary across companies, sectors, and countries. Furthermore, studies on logistics productivity incorporate index criteria identified by AEMLI. The literature examining the AEMLI index as a research topic has been prioritized in the initial review. In this context, Sawant (2013) applied the AEMLI to evaluate logistics infrastructure in India. Argyrou (2014), utilizing AEMLI to analyze logistics performance in Bangladesh, concluded that when local companies do not implement international supply chain management standards, logistics services are predominantly provided by foreign carriers and third-party logistics, resulting in joint venture agreements with local Bangladeshi parties. Beysenbaev (2018) investigated the importance of effective logistics and transport systems at the country level within the current international trade model. Al-Ababneh et al. (2021) examined the integration capabilities of national logistics systems in developing countries. The authors employed statistical analysis, indices, graphical and analytical methods, structural dynamic forecasting techniques, and comparisons in their studies. Kara et al. (2022) weighted the values of the AEMLI indicators using the ENTROPY method and utilized the MABAC method for ranking alternatives. Kara (2022) aimed to determine the domestic and international logistics opportunity efficiency levels of countries based on their market potentials, considering the AEMLI index. The author utilized data envelopment analysis and regression analyses in this study. Özekenci (2023) similarly employed SWARA, CRITIC, and CoCoSo methods for his research. Research utilizing MCDM methods in logistics and logistics performance measurement is summarized in Table 1.

Table 1. MCDM approach in logistics and logistics performance measurement

Author(s)	*Content*	*Method(s)*
Yalçın and Ayvaz (2020)	Logistics performance for Türkiye, Greece, Bulgaria, Georgia, and Iran	FAHP and F-TOPSIS
Alazzawi and Zak (2020)	Designing sustainable logistics corridors and supplier selection	ELECTRE III/IV and AHP
Ulutaş and Karaköy (2021)	Examining the logistics performance index values of transition economy countries	G-SWARA and G-MOORA
Korucuk (2021)	Comparative analysis of logistics performance elements in Ordu and Giresun provinces	CRITIC
Stević et al. (2021)	A proposal for customer-oriented key performance indicators (CKPIs) to determine reverse logistics quality	DELPHI, FUCOM and SERVQUAL
Altıntaş (2021)	Evaluating the logistics performance of EU countries	CRITIC, WASPAS and COPRAS
Zhang et al. (2021)	Identification of logistics center for the belt and road initiative	GRA and TOPSIS
Eren (2021)	Performance analysis of firms operating in the logistics sector	ENTROPY, CRITIC, SD and MULTIMOORA
Luyen and Thanh (2022)	Selecting and evaluating logistics service providers	SERVQUAL, FAHP and TOPSIS
Meśić et al. (2022)	Evaluating the logistics performance of Western Balkan countries	CRITIC and MARCOS
Özdağoğlu et al. (2022)	Ranking countries according to logistics assessment criteria	MAUT, TOPSIS, MOORA, MAIRCA, MABAC, WSM and WPM
Özbek and Özekenci (2023)	Investigating digital logistics market performance in developing countries	LOPCOW, MAUT, TOPSIS, MARCOS and CoCoSo
Miśkić et al. (2023)	Evaluating the logistics performance index of EU countries with emphasis on the importance of criteria	MEREC and MARCOS
Pala (2023)	Comparative analysis of logistics performance between Türkiye and the Visegrád Group	MEREC-Corr and SAW
Barasin et al. (2024)	Performance evaluation of retail warehouses	G-BWM and RATMI
Pehlivan (2024)	Integrated FCM/MCDM methodology for evaluating the logistics performance index	SAM, TOPSIS, MOORA, ARAS and FCM/MCDM

Upon reviewing Table 1, it is evident that studies utilizing the MCDM approach are prominently featured in the literature on logistics and logistics performance analysis. Studies integrating the MEREC, MABAC, or MAIRCA methods comprehensively are summarized and presented in Table 2.

Table 2. Studies applying the integrated MEREC, MABAC, or MAIRCA methods

Author(s)	*Content*	*Method(s)*
Kaya (2020)	Assessing the impact of Covid-19 on countries' sustainable development levels	MABAC, MAIRCA and WASPAS
Arsu and Ayçin (2021)	Ranking the OECD countries in economic, social, and environmental aspects	CRITIC, MAIRCA, MABAC, MARCOS, WASPAS, and
Özçalıcı (2022)	Evaluation of asset allocation in portfolio management	MEREC, MABAC and MAIRCA
Ersoy (2022)	Examinating the innovation performance in OECD and EU member countries	MEREC and MARCOS
Shanmugasundar et al. (2022)	Optimal selection of spray painting robots	MEREC, CODAS, COPRAS, CoCoSo and MABAC
Işık (2022)	The impact of Covid-19 on the performance of the participation banking sector	MEREC, PSI and MAIRCA
Ecer and Ayçin (2023)	Evaluating the innovation performance in G7 countries	MEREC, CODAS, MABAC, MARCOS, CoCoSo, WASPAS and MAIRCA

Upon reviewing Table 2, it is evident that integrated applications of methods are prevalent in the literature. Moreover, the MEREC, MABAC, and MAIRCA methods have found their place in the literature both in ranking countries and economic integrations, as well as in logistics-related issues (Jusufbašić, 2023; Torkayesh et al., 2023; Chejarla et al., 2022; Tian et al., 2023). Upon reviewing the literature, it is evident that studies frequently address topics related to the LPI. However, there is notable scarcity in research specifically focusing on the AEMLI. While existing studies critique the practice of unweighted logistics ranking, they also contribute to the formulation of the LPI within their scope. Furthermore, it is observed that there are fewer studies addressing the aspects of MEREC, MABAC, and MAIRCA in relation to logistics productivity. Therefore, this study stands out from other literature due to its analysis conducted on AEMLI. It is hoped that the study will contribute to the literature through its use of integrated methods.

3. METHODOLOGY

The need to transform data into results and arguments that support more informed and better decision-making has been increasing each year (Martyn and Kadziński, 2023). The concept of decision-making is defined as the process of selecting or ranking one or more options among available alternatives that provide the solution to a encountered problem or achieve specific goals based on established criteria (Esmeray and Özveri, 2023). The decision-making process generally consists of four vital sequential steps: problem identification, needs assessment, goal setting, and determination of evaluation criteria (Baker et al., 2002: 2-5; Top and Bulut, 2022). However, decision-making often involves a complex and multi-criteria decision-making process. MCDM provides a suitable methodology for evaluating such problems. The MCDM process, which creates a framework to structure problems and facilitate the selection of the best alternative from available options, consists of six steps (Opricovic and Tzeng, 2004; Top and Bulut, 2022):

1. Establishing evaluation criteria that relate capabilities to objectives,
2. Identifying alternatives to achieve objectives,
3. Evaluating alternatives based on criteria,
4. Applying a normative multi-criteria analysis method,
5. Determining the best alternative,
6. Iterating the process to achieve an optimal solution if a final solution is not reached.

The critique in this study focuses on the equal weighting of criteria in the construction of the AEMLI index and the absence of any preference for weighting methods. Variable or criteria weighting is crucial for determining the priorities of criteria at different levels of importance, considering the impact of each criterion, enhancing accuracy and reliability in mathematical modeling, improving performance, and suitability for developing strategies based on specific outcomes. Therefore, the study utilized MCDM methods. This section introduces the MEREC method utilized for weighting the criteria, along with the MABAC and MAIRCA methods employed for ranking alternatives.

3.1. Calculating the Weights of Criteria Through the MEREC Method

This study employs the MEREC method for the criteria weighting process, which quantitatively assesses the weights based on the removal effects of criteria, as supported by the existing literature. The MEREC method is categorized as an objective approach within the spectrum of criteria weighting techniques. Developed by Keshavarz-Ghorabaee et al. (2021), this method derives weights by analyzing the implications of criterion removal on decision-making. The steps of the MEREC method are presented below.

In Equation 1, m represents the number of alternatives, while n denotes the number of criteria.

$$X = \begin{bmatrix} x_{11} & x_{12} & x_{1n} \\ x_{21} & x_{22} & x_{2n} \\ \dots & \dots & \dots \\ x_{m1} & x_{m2} & x_{mn} \end{bmatrix} \tag{1}$$

The elements of the decision matrix are subjected to linear normalization, and the normalized values for benefit-type criteria are calculated using Equation 2 (Ersoy, 2022).

$$n_{ij}^{x} = \left\{ \frac{\min_{k} x_{kj}}{x_{ij}} ; for\ benefit\ type\ criteria \right. \tag{2}$$

In Equation 2, n_{ij}^{x} represents the elements of the normalization matrix. Subsequently, the calculation of the overall performance values of alternatives (S_i) is conducted (Equation 3).

$$S_i = ln\left(1 + \frac{1}{m}\sum_{j=1}^{n}\left\|ln\left(n_{ij}^{x}\right)\right\|\right) \tag{3}$$

In Equation 3, the overall performance values of the alternatives are calculated using a logarithmic measure with a non-linear function. The performance of alternatives, where the effect of the relevant criterion is disregarded (S'_{ij}) is computed as depicted in Equation 4. In the MEREC method, when calculating the weight of a criterion, the focus is on the change in the total criterion weight when that criterion is excluded (Noyan, 2023).

$$S'_{ij} = ln\left(1 + \frac{\sum_{j=1, j\neq k}^{n}\left(n_{ij}^{x}\right)}{n}\right)\right) \tag{4}$$

Based on the findings obtained from Equations 3 and 4, the values E_j, which indicate the removal effect of criterion j, are obtained by summing the absolute differences. The process is represented in the model outlined in Equation 5.

$$E_j = \sum_i \left|S'_{ij} - S_i\right| \tag{5}$$

Utilizing the model presented in Equation 6, the objective weights of the criteria are determined. In the model, w_j denotes the weight of the j-th criterion.

$$w_j = \frac{E_j}{\sum_k E_k} \tag{6}$$

In this study, the authors articulate several reasons for their preference for the MEREC method in determining criteria weights. First, the MEREC method minimizes errors arising from subjectivity in the decision-making process, as it does not require subjective inputs from decision-makers when establishing the weights of criteria (Keshavarz-Ghorabaee et al., 2021). Furthermore, it is posited that the results yield greater consistency and reliability due to their data-driven nature. Unlike other multi-criteria decision-making (MCDM) methods, such as AHP or ANP, the MEREC method does not necessitate that decision-makers provide preferences or engage in pairwise comparisons, thereby rendering it a simpler and more consistent approach. The MEREC method is widely recognized in the literature across various fields and is regarded as a valuable and applicable strategy, particularly in sectors such as logistics, where dynamic and complex decision-making is essential.

3.2. Ranking the Alternatives Through the MABAC and MAIRCA Methods

Following the determination of criterion weights through the MEREC method, the MABAC and MAIRCA methods were employed for ranking alternatives. The authors' preference for the MABAC-MAIRCA approach is primarily attributed to the significant advantages both methods offer in terms of flexibility, comprehensive evaluation, and transparency in the multi-criteria decision-making (MCDM) process. These methods are particularly effective in contexts that involve complex multi-criteria decisions. The MABAC method is noted for providing consistent results, even when there are changes in the measurement units used to represent the criteria values of the alternatives. Moreover, the algorithm of the MABAC method is well-suited for addressing multi-criteria problems that involve a large number of criteria and alternatives, due to its relatively straightforward mathematical formulation, which remains manageable as the number of alternatives and criteria increases (Torkayesh et al., 2023). A distinct advantage of the MAIRCA method, compared to other approaches, is its capacity to accommodate both qualitative and quantitative objectives

(Trung and Thinh, 2021). The relative simplicity of these methods provides a significant advantage over more complex alternatives (Alıcı and Ertuğrul, 2024).

3.2.1. MABAC Method

The MABAC method was introduced to the literature by Pamućar and Ćirović (2015). This method evaluates decision alternatives based on distances from the border approximation areas of criterion functions (Milosavljević et al., 2018; Çınaroğlu, 2020). The procedural steps of the method are outlined below. The initial step involves constructing a decision matrix comprising m alternatives and n criteria, with the matrix representation being consistent with that in Equation 1. Following the establishment of the decision matrix, a normalization process is conducted. The model presented in Equation 7 is employed for benefit-type criteria.

$$n_{ij} = \frac{x_{ij} - x_i^-}{x_i^+ - x_i^-} \tag{7}$$

In Equation 7, x_i^+ represents the maximum values of the columns of the decision matrix, while x_i^- denotes the minimum values. To obtain the weighted decision matrix, the notation in Equation 8 is utilized.

$$v_{ij} = w_i * (n_{ij} + 1) \tag{8}$$

Following the creation of the weighted decision matrix, the border approximation area for each criterion is determined according to the Equation 9.

$$g_i = \left(\prod_{j=1}^{m} v_{ij}\right)^{\frac{1}{m}} \tag{9}$$

The border approximation area matrix is computed using the model presented in Equation 10.

$$G = [g_1, g_2, \dots, g_n] \tag{10}$$

The distances of the alternatives from the border approximation area are calculated using the distance matrix from the border approximation area. The model representation for constructing the matrix is shown in Equation 11.

$$Q = V - G = \begin{bmatrix} v_{11} - g_1 & v_{12} - g_2 & v_{1n} - g_n \\ v_{21} - g_1 & v_{22} - g_2 & v_{2n} - g_n \\ \dots & \dots & \dots \\ v_{m1} - g_1 & v_{m2} - g_2 & v_{mn} - g_n \end{bmatrix} ; Q = \begin{bmatrix} q_{11} & q_{12} & q_{1n} \\ q_{21} & q_{22} & q_{2n} \\ \dots & \dots & \dots \\ q_{m1} & q_{m2} & q_{mn} \end{bmatrix} \tag{11}$$

The conditions for each alternative, based on their border approximation area, are determined using Equation 12.

$$A_i \in \begin{cases} G^+ \; if \; q_{ij} > 0 \\ G \; if \; q_{ij} = 0 \\ G^- \; if \; q_{ij} < 0 \end{cases} \tag{12}$$

According to Equation 12, for any alternative A_i, the condition $q_{ij} > 0$ signifies the proximity of A_i to the ideal alternative, while $q_{ij} < 0$ indicates the proximity of A_i to the negative ideal alternative. The criterion function (S_i) represents the sum of distances of each alternative from the border approximation area which is calculated using the model presented in Equation 13.

$$S_i = \sum_{j=1}^{n} q_{ij} \; ; i = 1,2, \dots, m \; ve \; j = 1,2, \dots, n \tag{13}$$

3.2.2. MAIRCA Method

The alternatives are ranked in descending order based on their criterion function values, and the alternative with the highest criterion function value is identified as the optimal alternative. In this study, the MAIRCA method was chosen as the second method for ranking alternatives. Introduced to the MCDM literature by Gigović et al. (2016), MAIRCA is a method based on identifying gaps between theoretical and real rankings. By summing the gaps for each criterion, a total gap is obtained for each decision alternative. At the end of the application process, the alternative with values closest to the ideal rankings across most criteria, or in other words, the alternative with the least total gap value, is determined as the best alternative. The procedural steps and notation representations of the method are detailed below (Pamućar et al., 2017; Pamućar et al., 2018; Ayçin, 2020). Since the method's decision matrix is represented identically to Equation 1, it has not been reiterated at this stage. Among the assumptions of the method is that the decision-maker does not have any priority in the alternative selection process. Thus, the priority P_{Ai} of alternative A_i, where m is the total number of alternatives, is calculated using the notation in Equation 14.

$$P_{Ai} = \frac{1}{m} \; ; \; \sum_{i=1}^{m} P_{Ai} = 1 \; ; i = 1,2, \dots, m \tag{14}$$

In the MAIRCA method, it is assumed that the decision-maker is equally distant from each alternative. This scenario is modeled in Equation 15.

$$P_{A1} = P_{A2} = \cdots = P_{Am} \tag{15}$$

Equation 16 presents the model for constructing the theoretical evaluation matrix to represent the matrix elements t_{pij}.

$$T_p = \begin{bmatrix} P_{\mathrm{A1}} * w_1 & P_{\mathrm{A1}*} w_2 & P_{\mathrm{A1}} * w_n \\ P_{\mathrm{A2}} * w_1 & P_{\mathrm{A2}} * w_2 & P_{\mathrm{A2}} * w_n \\ \dots & \dots & \dots \\ P_{\mathrm{Am}} * w_1 & P_{\mathrm{Am}} * w_2 & P_{Am} * w_n \end{bmatrix} \tag{16}$$

The application proceeds with defining the real evaluation matrix (T_r), which is derived from the initial decision matrix and theoretical evaluation matrix (T_p). The elements of this matrix are calculated using the notation shown in Equation 17 for benefit type criteria.

$$t_{rij} = t_{pij} * \left(\frac{x_{ij} - x_{ij}^{-}}{x_{ij}^{+} - x_{ij}^{-}}\right) \tag{17}$$

In Equation 17, x_{ij}^{+} represents the maximum value taken by criterion j., while x_{ij}^{-} represents the minimum value. The real evaluation matrix obtained from these calculations is presented in Equation 18.

$$T_r = \begin{bmatrix} t_{\mathrm{r11}} & t_{\mathrm{r12}} & t_{\mathrm{r1}n} \\ t_{\mathrm{r21}} & t_{\mathrm{r22}} & t_{\mathrm{r2}n} \\ \dots & \dots & \dots \\ t_{rm1} & t_{rm2} & t_{rmn} \end{bmatrix} \tag{18}$$

The total gap matrix is computed using the model shown in Equation 19.

$$G = T_p = T_r = \begin{bmatrix} g_{11} & g_{12} & g_{1n} \\ g_{21} & g_{22} & g_{2n} \\ \dots & \dots & \dots \\ g_{m1} & g_{m2} & g_{mn} \end{bmatrix} ; \; g_{ij} = t_{pij} - t_{rij} \, , g_{ij} \in [0, \infty) \tag{19}$$

In the MAIRCA method, if an alternative has an equal and non-zero difference between its theoretical and real evaluation for a criterion, the gap will be zero. In this case, the alternative is considered an ideal alternative for that criterion. Conversely, if an alternative has an equal difference of zero between its theoretical and real evaluations for a criterion, it is evaluated as the worst alternative for that criterion. The value of the criterion functions is calculated using the model in Equation 20.

$$Q_i = \sum_{j=1}^{n} g_{ij} \; ; i = 1,2, \dots, m \tag{20}$$

The Q_i values obtained from Equation 20 are sorted in ascending order to achieve the ranked results of the alternatives.

4. FINDINGS

The data used in the study were compiled as secondary data from Index journals of Agility by the authors. The study period was determined as 2021-2023. During this period, AEMLI presented data using equal weights of 25% across four criteria. This situation creates limitations for the study. Additionally, in order to verify the effectiveness of the methods and highlight the importance of weighting, the study included the top 15 countries from the AEMLI index annually from 50 countries. This aspect is also noted as another limitation of the research. The similarity of factors influencing logistics indicators across the top 15 countries is considered among the motivating factors for selecting alternatives in the study. The countries listed are China, India, United Arab Emirates, Malaysia, Indonesia, Saudi Arabia, Vietnam, Qatar, Thailand, Mexico, Türkiye, Chile, Russia, Bahrain, Kuwait, Jordan, Brazil, and Oman. All unit values of the criteria used in the study are presented in index/ratio form. The criteria, alternatives, and other descriptive information used in the study are shown in Table 3.

Table 3. Information regarding the dataset

Criteria	*Abbreviations*	*Optimization Direction*	*Abbreviations of Countries*
Domestic Opportunities	DO	Max	China (CHN), India (IND), United Arab Emirates (UAE), Malaysia (MYS), Indonesia (IDN), Saudi Arabia (SAU), Vietnam (VNM), Qatar (QAT), Thailand (THA), Mexico (MEX), Turkiye (TUR), Chile (CHL), Russia (RUS), Bahrain (BHR), Oman (OMN), Kuwait (KWT), Jordan (JOR), Brazil (BRA)
International Opportunities	IO	Max	
Business Fundametals	BF	Max	
Digital Readiness	DR	Max	

In this study, the normalized decision matrix and sample solution for the year 2021 used in determining the criterion weights are presented under this heading. The solution and procedural steps for other years can be found in the appendices section of the study. In this study, the selected fifteen countries primarily consist of the top fifteen countries each year during the examined period. These countries are notable for their high economic growth potential and dynamic markets. The strategic trade positions of the countries have also been taken into consideration during their selection. For instance, countries such as the United Arab Emirates and Qatar have become significant centers of international trade by positioning themselves strategically between the Middle East and Asia. The differing economic structures and development levels of the selected countries indicate that using equal weights in the logistics index may be problematic. For example, while countries like Malaysia and Indonesia face various challenges as emerging markets, countries like the United Arab Emirates possess more developed infrastructure. The levels of digital readiness among these countries also vary. All of these nations are emerging markets that play a crucial role in the global economic system. There are significant differences in economic structure, infrastructure, governance policies, and digital maturity levels among the countries. These differences and similarities play an important role in the evaluation of the logistics index. Employing equal weights may overlook the unique challenges and advantages of the countries, potentially leading to misleading results. By analyzing these countries, the aim is to develop a more precise and accurate logistics index. Such an approach provides more meaningful insights for policymakers and businesses, creating a more effective foundation for decision-making processes.

4.1. Calculating the Weights of Criteria Through the MEREC Method

As presented in Table 4, the normalization matrix for the year 2021 is provided before outlining the steps of the MEREC method.

Table 4. The normalization matrix (2021)

Alternatives	*DO*	*IO*	*BF*	*DR*
CHN	0.5703	0.4800	0.7266	0.7117
IND	0.6080	0.6473	0.8607	0.7656
UAE	0.8728	0.8168	0.5576	0.5979
MYS	0.9154	0.7905	0.6264	0.7020
IDN	0.7681	0.7866	0.8651	0.7975
SAU	0.9103	0.8494	0.6287	0.7298
QAT	0.8411	0.9571	0.6445	0.7914
THA	0.9493	0.7787	0.8814	0.7890
MEX	0.8791	0.7313	1.0000	0.9556
TUR	0.9223	0.7973	0.8739	0.8658
VNM	0.9701	0.7787	0.9361	0.8974
CHL	1.0000	0.9052	0.7155	0.8404
RUS	0.9365	0.8254	0.9310	0.8761
OMN	0.9898	0.9571	0.7066	0.9069
BHR	0.9760	1.0000	0.7027	1.0000

After normalizing the decision matrix, the overall performance values of the alternatives are computed. These values are presented in Table 5.

Table 5. Overall performance values of the alternatives (S_i) (2021)

Alternatives	S_i	Alternatives	S_i
CHN	0.3979	*MEX*	0.115
IND	0.2907	*TUR*	0.1368
UAE	0.3069	*VNM*	0.1077
MYS	0.2517	*CHL*	0.1416
IDN	0.1978	*RUS*	0.1091
SAU	0.2304	*OMN*	0.1176
QAT	0.2009	*BHR*	0.0901
THA	0.1539		

The process continues with the calculation of the overall performance values obtained by removing the effects of the criteria using the MEREC method. These values are presented in Table 6.

Table 6. Overall performance values of the alternatives by removing each criterion (S'_{ij}) (2021)

Alternatives	*DO* (S'_{ij})	*IO* (S'_{ij})	*BF* (S'_{ij})	*DR* (S'_{ij})
CHN	0.2989	0.2664	0.3428	0.3391
IND	0.1931	0.2059	0.2623	0.2395
UAE	0.2816	0.2690	0.1933	0.2075
MYS	0.2344	0.2050	0.1564	0.1805
IDN	0.1422	0.1473	0.1677	0.1503
SAU	0.2115	0.1974	0.1337	0.1658
QAT	0.1649	0.1919	0.1068	0.1519
THA	0.1427	0.0988	0.1264	0.1017
MEX	0.0858	0.0427	0.1150	0.1048
TUR	0.1190	0.0861	0.1070	0.1048
VNM	0.1008	0.0499	0.0927	0.0831
CHL	0.1416	0.1197	0.0661	0.1031
RUS	0.0943	0.0652	0.0930	0.0790
OMN	0.1153	0.1078	0.0373	0.0956
BHR	0.0845	0.0901	0.0061	0.0901

The weights of the criteria are derived based on the notation outlined in the methodology section. These results are presented in Table 7 for the year 2021.

Table 7. Summation of absolute deviations and the final weights of the criteria (2021

Values	*DO*	*IO*	*BF*	*DR*
E_j	0.4375	0.7050	0.8416	0.6511
w_j	0.1660	0.2675	0.3194	0.2471

The weights derived from the MEREC method calculations for the year 2021, as presented in the example above, are provided here. The calculation steps for subsequent years can be found in the Appendices. The results for all years are sumamrized in the following table. In this study, the criterion weights obtained using the MEREC method for prioritization are comparatively presented in Table 8 alongside AEMLI results.

Table 8. Criteria weights and the comparison of these weights (2021-2023)

Criteria	*2021*	*2022*	*2023*	*AEMLI*
DO	0.1660	0.1696	0.1580	0.25
IO	0.2675	0.2657	0.2796	0.25
BF	0.3194	0.3644	0.4302	0.25
DR	0.2471	0.2003	0.1321	0.25

When examining Table 8, it is observed that the criterion with the highest importance weight for all years is BF, while the criterion with the lowest importance weight is DO for the years 2021 and 2022, and DR for 2023. Furthermore, the average highest difference among criteria is calculated as 0.2154, indicating that the criteria should not be equally weighted. The consistent highest weight score of the business fundemetal criterion across all periods is interpreted as aligning with expectations and theory. In this context, the logistics development of countries is seen as a reflection of systematic approaches to operational issues (Nekhoroshkov et al., 2021). Additionally, logistics costs for businesses exert pressure not only on the logistics department but also on overall business economics (Majerćak et al., 2013). In the study, the domestic opportunities criterion has been identified as having the lowest weight score for the years 2021 and 2022. This period falls within the pandemic era, which significantly impacted global trade dynamics.

The risk factor crucial for logistics productivity has become more pronounced, particularly with the Covid-19 pandemic, exposing new challenges beyond traditional supply and demand uncertainties. The seamless operation of logistics and the economy is crucial as all sectors are interconnected through complex supply chains and logistics networks (Choi, 2021; Rokicki et al., 2022; Montoya-Torres, 2023). In 2023, the digital readiness criterion is observed to have the lowest weight score. This is associated with the widespread adoption of new technologies in logistics, such as big data, automation, and the Internet of Things. Technical personnel face constraints in adjusting their digital literacy skills to fit the new systems of organizations (Azhigali, 2023).

4.2. Results of the MABAC Method for Ranking Alternatives

In this study, the normalization matrix and example solutions for ranking alternatives using the MABAC method for the year 2021 are presented in this section. The solutions and procedural steps for subsequent years can be found in the Appendix of the study.

Table 9. The normalization matrix (2021)

Alternatives	*DO*	*IO*	*BF*	*DR*
CHN	1.0000	1.0000	0.4742	0.6023
IND	0.8556	0.5030	0.2039	0.4553
UAE	0.1935	0.2071	1.0000	1.0000
MYS	0.1226	0.2446	0.7518	0.6311
IDN	0.4005	0.2505	0.1966	0.3775
SAU	0.1308	0.1637	0.7445	0.5504
QAT	0.2507	0.0414	0.6953	0.3919
THA	0.0708	0.2623	0.1695	0.3977
MEX	0.1826	0.3393	0.0000	0.0692
TUR	0.1117	0.2347	0.1818	0.2305
VNM	0.0409	0.2623	0.0860	0.1700
CHL	0.0000	0.0966	0.5012	0.2824
RUS	0.0899	0.1953	0.0934	0.2104
OMN	0.0136	0.0414	0.5233	0.1527
BHR	0.0327	0.0000	0.5332	0.0000

In this study, the decision matrix utilized in the MEREC method for 2021 is not reiterated, as it is applicable to all calculations; the discussion proceeds directly to the presentation of the normalization matrix. The method then advances by calculating the weighted normalization matrix for the MABAC method. These values are presented in Table 10.

Table 10. The weighted normalization matrix (2021)

Alternatives	*DO*	*IO*	*BF*	*DR*
CHN	0.3320	0.5350	0.4708	0.3959
IND	0.3081	0.4021	0.3845	0.3596
UAE	0.1981	0.3229	0.6387	0.4942
MYS	0.1864	0.3329	0.5595	0.4030
IDN	0.2325	0.3345	0.3821	0.3404
SAU	0.1877	0.3113	0.5571	0.3831
QAT	0.2076	0.2786	0.5414	0.3439
THA	0.1778	0.3377	0.3735	0.3454
MEX	0.1963	0.3583	0.3194	0.2642
TUR	0.1846	0.3303	0.3774	0.3041
VNM	0.1728	0.3377	0.3468	0.2891
CHL	0.1660	0.2934	0.4795	0.3169
RUS	0.1809	0.3198	0.3492	0.2991
OMN	0.1683	0.2786	0.4865	0.2848
BHR	0.1714	0.2675	0.4897	0.2471

The process continues with the creation of the border approximation area matrix for the MABAC method and the determination of its values. The obtained results are presented in Table 11.

Table 11. Determining the border approximation area (2021)

Value	*DO*	*IO*	*BF*	*DR*
g_i	0.2001	0.3312	0.4410	0.3328

The values obtained from Table 11 are utilized to calculate the distances of the decision alternatives from the border approximation area. In the example for the year 2021, these results are presented in Table 12.

Table 12. Calculating the distance of the alternatives from the border approximation area (2021)

Alternatives	*DO*	*IO*	*BF*	*DR*
CHN	0.1319	0.2038	0.0298	0.0631
IND	0.1080	0.0709	-0.0565	0.0268
UAE	-0.0020	-0.0083	0.1977	0.1614
MYS	-0.0137	0.0017	0.1185	0.0702
IDN	0.0324	0.0033	-0.0589	0.0076
SAU	-0.0124	-0.0199	0.1161	0.0503
QAT	0.0075	-0.0526	0.1004	0.0111
THA	-0.0223	0.0065	-0.0675	0.0126
MEX	-0.0038	0.0271	-0.1217	-0.0686
TUR	-0.0155	-0.0009	-0.0636	-0.0287
VNM	-0.0273	0.0065	-0.0942	-0.0437
CHL	-0.0341	-0.0378	0.0384	-0.0159
RUS	-0.0192	-0.0115	-0.0918	-0.0337
OMN	-0.0318	-0.0526	0.0455	-0.0480
BHR	-0.0287	-0.0637	0.0486	-0.0857

The MABAC method is concluded by calculating the S_i values used for ranking. In the example for the year 2021, the results are presented in Table 13.

Table 13. Calculating the values of the criterion functions for the alternatives (2021)

Alternatives	S_i	Alternatives	S_i
CHN	0.4287	*MEX*	-0.167
IND	0.1491	*TUR*	-0.1088
UAE	0.3488	*VNM*	-0.1587
MYS	0.1767	*CHL*	-0.0494
IDN	-0.0156	*RUS*	-0.1562
SAU	0.1341	*OMN*	-0.0869
QAT	0.0665	*BHR*	-0.1294
THA	-0.0708		

The results obtained for all years related to the MABAC method are presented in a consolidated format in Table 14.

Table 14. Calculating the values of the criterion functions for the alternatives (2021-2023)

Alternatives	*2021*	*2022*	*2023*
CHN	0.4287	0.4241	0.4530
IND	0.1491	0.2607	0.2163
UAE	0.3488	0.3229	0.2766
MYS	0.1767	0.1466	0.1627
IDN	-0.0156	-0.0266	0.0199
SAU	0.1341	0.1107	0.0968
VNM	-0.1587	-0.1573	-0.0457
QAT	0.0665	0.1065	0.0452
THA	-0.0708	-0.0928	-0.1004
MEX	-0.1670	-0.2110	-0.1140
TUR	-0.1088	-0.1466	-0.1287
CHL	-0.0494	-0.0784	-0.0463
RUS	-0.1562	*	-0.1733
BHR	-0.1294	-0.1005	*
OMN	-0.0869	-0.0474	*
KWT	*	-0.1466	*
BRA	*	*	-0.2537
JOR	*	*	-0.0885

4.3. Results of the MAIRCA Method for Ranking Alternatives

In this study, example solutions for ranking alternatives using the MAIRCA method for the year 2021 are presented in this section. Solutions and procedural steps for subsequent years can be found in the appendix of the study. The process continues with the definition of the real evaluation matrix for the MAIRCA method, with the results for the year 2021 are presented in Table 15.

Table 15. Calculating the final values of criteria functions by alternatives (2021)

Alternatives	*DO*	*IO*	*BF*	*DR*
CHN	0.0111	0.0178	0.0101	0.0099
IND	0.0095	0.0090	0.0043	0.0075
UAE	0.0021	0.0037	0.0213	0.0165
MYS	0.0014	0.0044	0.0160	0.0104
IDN	0.0044	0.0045	0.0042	0.0062
SAU	0.0014	0.0029	0.0159	0.0091
QAT	0.0028	0.0007	0.0148	0.0065
THA	0.0008	0.0047	0.0036	0.0066
MEX	0.0020	0.0061	0.0000	0.0011
TUR	0.0012	0.0042	0.0039	0.0038
VNM	0.0005	0.0047	0.0018	0.0028
CHL	0.0000	0.0017	0.0107	0.0047
RUS	0.0010	0.0035	0.0020	0.0035
OMN	0.0002	0.0007	0.0111	0.0025
BHR	0.0004	0.0000	0.0114	0.0000

In the MAIRCA method, the total gap matrix for the year 2021 has been constructed as presented in Table 16.

Table 16. Calculating the total gap matrix (2021)

Alternatives	*DO*	*IO*	*BF*	*DR*
CHN	0.0000	0.0000	0.0112	0.0066
IND	0.0016	0.0089	0.0169	0.0090
UAE	0.0089	0.0141	0.0000	0.0000
MYS	0.0097	0.0135	0.0053	0.0061
IDN	0.0066	0.0134	0.0171	0.0131
SAU	0.0096	0.0149	0.0054	0.0074
QAT	0.0083	0.0171	0.0065	0.0100
THA	0.0103	0.0132	0.0177	0.0099
MEX	0.0090	0.0118	0.0213	0.0153
TUR	0.0098	0.0136	0.0174	0.0127
VNM	0.0106	0.0132	0.0195	0.0137
CHL	0.0111	0.0161	0.0106	0.0118
RUS	0.0101	0.0144	0.0193	0.0130
OMN	0.0109	0.0171	0.0101	0.0140
BHR	0.0107	0.0178	0.0099	0.0165

The $\mathrm{Q_i}$ values derived from the MAIRCA method are presented in Table 17. These values serve as the basis for ranking.

Table 17. Calculating the criteria function (2021)

Alternatives	Q_i	Alternatives	Q_i
CHN	0.0177	*MEX*	0.0575
IND	0.0364	*TUR*	0.0536
UAE	0.0231	*VNM*	0.0569
MYS	0.0345	*CHL*	0.0496
IDN	0.0474	*RUS*	0.0567
SAU	0.0374	*OMN*	0.0521
QAT	0.0419	*BHR*	0.0550
THA	0.0510		

The $\mathrm{Q_i}$ values obtained from the MAIRCA method are presented in Table 18, encompassing all years and all alternatives considered.

Table 18. Calculating the criteria function (2021-2023)

Alternatives	*2021*	*2022*	*2023*
CHN	0.0177	0.0168	0.0127
IND	0.0364	0.0277	0.0285
UAE	0.0231	0.0236	0.0245
MYS	0.0345	0.0353	0.0321
IDN	0.0474	0.0469	0.0416
SAU	0.0374	0.0377	0.0365
VNM	0.0569	0.0556	0.0460
QAT	0.0419	0.0380	0.0399
THA	0.0510	0.0513	0.0496
MEX	0.0575	0.0592	0.0505
TUR	0.0536	0.0549	0.0515
CHL	0.0496	0.0503	0.0460
RUS	0.0567	*	0.0545
BHR	0.0550	0.0518	*
OMN	0.0521	0.0483	*
KWT	*	0.0549	*
BRA	*	*	0.0599
JOR	*	*	0.0488

4.4. Integrated Comparative and Ranked Presentation of Results

In this study, the findings related to the MABAC and MAIRCA methods utilized for ranking alternatives, along with their comparison to AEMLI, are presented in this section. The results obtained from these methods and the AEMLI calculations are presented comparatively in Table 19.

Table 19. Results for all years according to all methods

	2021			*2022*			*2023*		
Countries	*MABAC*	*MAIRCA*	*AEMLI*	*MABAC*	*MAIRCA*	*AEMLI*	*MABAC*	*MAIRCA*	*AEMLI*
CHN	0.4287	0.0177	8.50	0.4241	0.0168	8.31	0.4530	0.0127	8.61
IND	0.1491	0.0364	7.21	0.2607	0.0277	7.43	0.2163	0.0285	7.21
UAE	0.3488	0.0231	6.72	0.3229	0.0236	6.59	0.2766	0.0245	6.49
MYS	0.1767	0.0345	6.32	0.1466	0.0353	6.16	0.1627	0.0321	6.17
IDN	-0.0156	0.0474	6.17	-0.0266	0.0469	6.08	0.0199	0.0416	6.16
SAU	0.1341	0.0374	6.14	0.1107	0.0377	6.07	0.0968	0.0365	6.05
VNM	-0.1587	0.0569	5.55	-0.1573	0.0556	5.52	-0.0457	0.0460	5.73
QAT	0.0665	0.0419	5.95	0.1065	0.0380	6.02	0.0452	0.0399	5.85
THA	-0.0708	0.0510	5.78	-0.0928	0.0513	5.67	-0.1004	0.0496	5.59
MEX	-0.1670	0.0575	5.74	-0.2110	0.0592	5.55	-0.1140	0.0505	5.60
TUR	-0.1088	0.0536	5.69	-0.1466	0.0549	5.49	-0.1287	0.0515	5.45
CHL	-0.0494	0.0496	5.55	-0.0784	0.0503	5.43	-0.0463	0.0460	5.39
RUS	-0.1562	0.0567	5.53	*	*	*	-0.1733	0.0545	5.34
BHR	-0.1294	0.0550	5.41	-0.1005	0.0518	5.31	*	*	*
OMN	-0.0869	0.0521	5.28	-0.0474	0.0483	5.46	*	*	*
KWT	*	*	*	-0.1466	0.0549	5.25	*	*	*
BRA	*	*	*	*	*	*	-0.2537	0.0599	5.29
JOR	*	*	*	*	*	*	-0.0885	0.0488	5.19

The ranked results obtained from the methods, along with the ranked values from the AEMLI calculations, are presented comparatively in Table 20. Upon examining Table 20, it is evident that the countries CHN, IND, UAE, and MYS consistently rank highest across all periods in the MABAC and MAIRCA ranking results, while VNM, MEX, BHR, and JOR tend to rank lowest. The findings from the MABAC and MAIRCA methods supporting each other in terms of their outcomes are considered indicative of the study's consistency. The obtained results in the study are further supported and exemplified by the literature. Saudi Arabia's ranking value was found to be higher in both the MABAC and MAIRCA results. Enhancing the logistics sector and improving its ranking were among the country's foremost targeted success factors outlined in its Vision 2030 initiative (Almalki and Alkahtani, 2022). Similarly, Chile's ranking according to the AEMLI results for the period 2021-2023 was 12-13, whereas it was 8-9 according to the MABAC and MAIRCA results. Chile is recognized for having the most efficient customs regime in the region as a consequence of its free trade agreements and trade practices with a total of 31 countries (T.C. Dış İşleri Bakanlığı, 2023). Since the early 2000s, Latin American countries have initiated campaigns to promote their national brands internationally, promoting exports, direct foreign investments, and tourism offers. Chile's slogan in building its brand, "Good for you" is particularly noted (Mino and Austin, 2022). Indonesia's results from the MABAC and MAIRCA methods show that they fall behind the AEMLI results. This discrepancy is associated with urban and national logistics challenges in the country, such as urbanization, traffic density, land conflicts, and inadequate readiness of agencies in logistics processes (Widodo et al., 2018). Kailaku et al. (2022) state that Indonesia's logistics performance lags behind most ASEAN countries, attributing this to high container handling costs due to the country's dependence on intra-island connections. Nurprihatin et al. (2021) emphasize the need for improved distribution routes and government policies to meet scarce demand, particularly in the food sector. Similarly, Vietnam's results from the MABAC and MAIRCA methods also lag behind the AEMLI results. The country faces logistical challenges primarily due to domestic logistics costs often exceeding those of imported goods (Nguyen et al., 2022). The logistics challenges stem from the multiple intermediaries involved in production, distribution, and increased operational costs and selling prices in sectors such as agriculture, forestry, and fisheries (Pham and Doan, 2020). Overall, the findings underscore the impact of weighted criteria on countries' logistics performances. This influence is reflected in the ranking outcomes, which align more closely with theoretical expectations.

Table 20. Comparing the alternatives

	2021			*2022*			*2023*		
Ranking	*MABAC*	*MAIRCA*	*AEMLI*	*MABAC*	*MAIRCA*	*AEMLI*	*MABAC*	*MAIRCA*	*AEMLI*
1	CHN	CHN	CHN	CHN	CHN	CHN	CHN	CHN	CHN
2	UAE	UAE	IND	UAE	UAE	IND	UAE	UAE	IND
3	MYS	MYS	UAE	IND	IND	UAE	IND	IND	UAE
4	IND	IND	MYS	MYS	MYS	MYS	MYS	MYS	MYS
5	SAU	SAU	IDN	SAU	SAU	IDN	SAU	SAU	IDN
6	QAT	QAT	SAU	QAT	QAT	SAU	QAT	QAT	SAU
7	IDN	IDN	QAT	IDN	IDN	QAT	IDN	IDN	QAT
8	CHL	CHL	THA	OMN	OMN	THA	VNM	VNM	VNM
9	THA	THA	MEX	CHL	CHL	MEX	CHL	CHL	MEX
10	OMN	OMN	TUR	THA	THA	VNM	JOR	JOR	THA
11	TUR	TUR	VNM	BHR	BHR	TUR	THA	THA	TUR
12	BHR	BHR	CHL	KWT	TUR	OMN	MEX	MEX	CHL
13	RUS	RUS	RUS	TUR	KWT	CHL	TUR	TUR	RUS
14	VNM	VNM	BHR	VNM	VNM	BHR	RUS	RUS	BRA
15	MEX	MEX	OMN	MEX	MEX	KWT	BRA	BRA	JOR

5. DISCUSSION and CONCLUSION

Logistics performance and efficiency are crucial for both countries and businesses. For businesses, logistics performance necessitates effective management of supply chain operations, storage, distribution, and customer service. This management is pivotal for cost reduction, improvement of delivery processes, and enhancement of customer satisfaction. In this context, logistics productivity enables better utilization of resources in operational processes. At the national level, logistics performance and efficiency influence national economic growth and the development of foreign trade. Well-functioning logistics systems contribute to increased trade volume and international competitiveness. Technological innovations and infrastructure investments enhance logistics productivity, thereby promoting economic growth and increasing the competitiveness of national economies. Therefore, integrated improvement of logistics performance and efficiency facilitates overall performance enhancement for both countries and businesses. This integration is also considered significant in arguments used by countries to attract investors or as evaluation criteria for investors assessing countries. The fragile nature of logistics performance gained increased significance following the attack on the World Trade Center on September 11, 2001. The risks contributing to this fragility are highly diverse and stem from sources both within and outside the supply chain (Wilson, 2007). Chopra and Sodhi (2004) identified these risks as delays, information and networking issues, forecasting, intellectual property, supply, customers, inventory, and capacity. While these categories can be further expanded, it is more appropriate and consistent to discuss this situation alongside the challenges that accompany these risks. Additionally, there are challenges that affect logistics performance, such as inadequate infrastructure, the ability to adapt to technology, uncertainty arising from demand forecasts, high transportation costs, and regulatory frameworks. Furthermore, it has been stated that logistics-related issues often originate from a global, competitive environment, constraints, social or ecological concerns, and deficiencies in information flows, information transfer, or well-integrated IT applications (Clausen et al., 2016; Wang, 2018). Logistics performance is vital for the seamless functioning of economies, and disruptions can create bottlenecks that negatively impact economic productivity and growth (Goel et al., 2021; Salvatore, 2020). In this context, the importance of logistics metrics is underscored. Logistics metrics play a critical role in enhancing logistics performance, ensuring efficiency, and overcoming related challenges. Identifying performance gaps in logistics, facilitating international comparisons, optimizing supply chain operations, and overcoming infrastructure challenges (effective logistics metrics also provide insights into where infrastructure investments are needed) are tasks accomplished through efficient logistics metric management. In this regard, the advantages of logistics metrics include data-driven decision-making, cost reduction, supplier satisfaction, and sustainability. Lai et al. (2004) argue that the intensifying global competition demands not individual performance but rather organizational excellence based on flawless inter-organizational collaboration. The continuous rise of global trade and many countries' desire to accelerate their integration into the global trading system relies not only on maintaining an open global economic system but also on enhancing the quantity and efficiency of support structures such as logistics services (Gani, 2017). Therefore, it is possible to express the growing importance of logistics metrics. Ultimately, logistics metrics enable countries to identify challenges, optimize supply chains, and enhance overall performance. Accurate measurement allows governments and businesses to respond quickly to inefficiencies, promote trade, and support economic development.

Trade, linked to the efficiency and productivity of logistics performance, is a critical factor in ensuring national and international competitiveness for countries. In this context, the positive economic and social impacts of growing sectors have been identified (Mešić et al., 2022). Indicators related to the logistics sector are utilized to enhance countries' trade capacities and increase their international competitiveness. These indicators guide both investors and countries in making strategic logistics decisions. The strategic importance lies in determining the country where logistics companies want to invest or which criteria logistics firms should focus more on (Ulutaş and Karaköy, 2019). AEMLI is considered a significant indicator, especially for emerging markets. The effectiveness of logistics services is directly related to expanding trade networks between countries, increasing foreign direct investments, and boosting economic growth (Çalık et al., 2023). This relationship underscores the importance of criterion weighting in complex evaluations such as logistics performance rankings, where different criteria weights and their contributions to the overall ranking are crucial references. Hence, in this study, sub-criteria of the AEMLI index were weighted using the MEREC method. The alignment of the importance levels derived from criterion weighting with the literature is interpreted as indicating the consistency of the study and the method. The study employed the MABAC and MAIRCA methods for ranking alternatives. It was observed that the rank positions of countries varied partially based on weighted criteria. This limitation is associated with AEMLI allocating 25% weight to four criteria during the period of 2021-2023. Consequently, it is anticipated that different results may be obtained over a broader period. Considering the examples of countries whose rankings have changed, the findings are interpreted as more consistent with the literature. Reviews of studies focusing on weighting other logistics performance indicators in the literature also support interpretations made in this study (Ulutaş and Karaköy, 2019; Mešić et al., 2022; Çalık et al., 2023; Gürler et al., 2024; Rezaei et al., 2018). Emerging markets encompass significant opportunities in logistics. Rapid economic growth in these markets facilitates increased consumer demand and the exploration of new markets. Accessing these new markets also entails adapting supply chain strategies. Optimizing new supply chains according to market dynamics is considered to create opportunities for countries. The need for infrastructure investments in logistics is crucial for stakeholders in the logistics sector and for enhancing the logistics productivities of countries. Thus, this study contributes by examining the AEMLI index, thereby differentiating itself from existing literature and contributing to it.

The AEMLI index reveals that Türkiye is among the key countries listed. In this context, this study will address aspects that emphasize the importance of logistics efficiency specifically concerning Türkiye. First and foremost, it is evident that Türkiye needs long-term visions and strategies to achieve higher rankings in international logistics rankings. Establishing a strategy such as a vision for 2030-2050-2060 (which can be named differently) is essential for strengthening Türkiye's logistics infrastructure and supporting sectoral development. Moreover, it is believed that Türkiye should focus more on urban transportation planning, traffic management, and the digitalization of logistics processes to find solutions to logistics challenges within its borders. To attract foreign investments, it is crucial for Türkiye to enhance its brand image and conduct more international promotional campaigns, as well as to participate actively in bilateral cooperation discussions. Additionally, to foster the development of exports and domestic trade, training and support programs should be established to enable local producers to deliver services that meet international standards. Alongside these programs, it is deemed essential to prioritize research and development activities in areas such as decarbonization, sustainability, and green logistics, in order to accelerate results and benefits. It is anticipated that with such strategies, Türkiye can enhance its logistics performance, becoming more competitive on the international stage.

Quantitative methods, by leveraging statistical and mathematical tools, provide a structured approach to analyzing complex datasets in social sciences, which enhances the robustness of research findings. These methods enable researchers to test hypotheses rigorously, offering more credible results that can inform both theoretical frameworks and practical applications. Furthermore, quantitative techniques allow for the replication of studies, contributing to the reliability and validity of research outcomes across different contexts. In logistics, MCDM methods are particularly valuable, as they facilitate the comparison of multiple decision criteria, ensuring a comprehensive evaluation of logistics performance. The ability of these methods to accommodate uncertainty and diverse scenarios makes them essential for both strategic decision-making and operational improvements in the logistics industry. In a MCDM problem, assigning equal weight to all criteria in logistics-related decisions can have several drawbacks, particularly for emerging markets. All logistics criteria do not carry the same level of importance depending on the context. For example, while cost may be critical for some markets, sustainability or speed may be more relevant in others. Equal weighting can obscure these differences, leading to suboptimal decisions that fail to align with the specific goals or strategic priorities of a company or market. Emerging markets often have distinct logistical challenges such as underdeveloped infrastructure, varying regulatory requirements, or different consumer preferences. In this case, assuming everything to be standard can be misleading. In summary, assigning equal weights to logistics-related criteria in MCDM problems may result in rigid and ineffective decision-making, particularly in emerging markets that require more nuanced and dynamic approaches tailored to local challenges and opportunities.

MCDM methods, with their ability to consider multiple criteria, evaluate alternatives under uncertainty or different scenarios, and impact process improvement, have found their place in the logistics sector as well as in other industries. Given the logistics sector's comprehensive and stakeholder-driven nature, and considering the unique characteristics specific to countries, there is a recommendation for greater inclusion of MCDM methods in the sector-specific literature. Particularly in recent times, studies focusing on logistics indicators and considering criterion weights have become increasingly prevalent. Acknowledging the variations among countries or firms, it is emphasized that identifying the determinants of logistics performance and efficiency through numerical methods is essential. Thus, the use of numerical methods, such as Path Analysis, to identify the determinants of logistics performance and efficiency is considered visionary for future studies. Last-mile delivery and green logistics have gained significant importance in today's context, particularly due to the rapid growth of e-commerce. In this regard, last-mile delivery offers several advantages, such as ensuring supplier and customer satisfaction, gaining competitive advantage, and facilitating cost management. Conversely, green logistics is characterized by its benefits related to sustainability, compliance with legal procedures, and effective reputation management for companies and countries. Both concepts are regarded as potential trends within contemporary literature. Last-mile delivery and green logistics are integral components of modern logistics strategies. These processes not only enhance customer satisfaction but also support environmental sustainability and help businesses remain competitive. In their research, Patella et al. (2021) suggest that the increasing number of publications on this topic in recent years indicates a growing academic interest in this field. Similarly, Eskandaripour and Boldsaikhan (2023) conclude that the challenges faced in efficient and green transportation methods align closely with the overall challenges in logistics. We posit that both areas hold significant potential for future literature and research endeavors.

Author Contributions

Elif Bulut: Literature review, Conceptualization, Methodology, Modelling, Data Curation, Analysis, Writing-original draft. *Seda Abacıoğlu:* Literature review, Conceptualization, Methodology, Modelling, Data Curation, Analysis, Writing-original draft

Conflict of Interest

No potential conflict of interest was declared by the authors.

Funding

Any specific grant has not been received from funding agencies in the public, commercial, or not-for-profit sectors.

Compliance with Ethical Standards

It was declared by the authors that the tools and methods used in the study do not require the permission of the Ethics Committee.

Ethical Statement

It was declared by the authors that scientific and ethical principles have been followed in this study and all the sources used have been properly cited.

REFERENCES

Agility (2022). "Agility Emerging Markets Logistics Index". https://www.agility.com/wp-content/uploads/2022/02/Agility-Emerging-Markets-Logistics-Index2022.pdf, (Access Date: 09.07.2024).

Agility (2023). "Agility Emerging Markets Logistics Index". https://www.agility.com/wp-content/uploads/2023/02/Agility-Emerging-Markets-Logistics-Index-2023-EN.pdf, (Access Date: 09.07.2024).

Agility (2024). "Agility Emerging Markets Logistics Index". https://emli.agility.com/wp-content/uploads/2024/02/Agility-Emerging-Markets-Logistics-Index-2024.pdf, (Access Date: 09.07.2024).

Al-Ababneh, H.A., Dumanska, I., Derkach, E., Sokhetska, A. and Kemarska, L. (2021). "Integration of Logistics Systems of Developing Countries into International Logistics Channels", *Acta Logistica,* 8(4), 329-340. https://doi.org/10.22306/al.v8i4.234

Alazzawi, A. and Żak, J. (2020). "MCDM/A Based Design of Sustainable Logistics Corridors Combined with Suppliers Selection: The Case Study of Freight Movement to Iraq", *Transportation Research Procedia,* 47*,* 577-584. https://doi.org/10.1016/j.trpro.2020.03.134

Alıcı, S.Y and Ertuğrul, İ. (2024). "Human Resources Management Application Selection with Fuzzy MAIRCA Method Based on Fuzzy PIPRECIA", *Pamukkale Üniversitesi İşletme Araştırmaları Dergisi,* 11(1), 67-81. https://doi.org/10.47097/piar.1427355

Almalki, M. and Alkahtani, M. (2022). "Allocation of Regional Logistics Hubs and Assessing Their Contribution to Saudi Arabia's Logistics Performance Index Ranking", *Sustainability,* 14(12), 7474.

Altıntaş, F.F. (2021). "Avrupa Birliği Ülkelerinin Lojistik Performanslarının CRITIC Tabanlı WASPAS ve COPRAS Teknikleri ile Analizi", *Türkiye Sosyal Araştırmalar Dergisi,* 25(1), 117-146.

Argyrou, K. (2014). "Exploring the Logistics Sector in Bangladesh: Opportunities, Threats and Practical Information", Netherlands Bangladesh Business Platform Published, Breukelen*.*

Arsu, T. and Ayçin, E. (2021). "Evaluation of OECD Countries with Multicriteria Decision-Making Methods in Terms of Economic, Social and Environmental Aspects", *Operational Research in Engineering Sciences: Theory and Applications,* 4(2), 55-78. https://doi.org/10.31181/oresta20402055a

Arvis,J.F., Wiederer, C.K., Ojala, L.M., Shepherd, B.A., Raj, A.U.L., Dairabayeva, K.S. and Kiiski, T.M.M. (2018) "Connecting to Compete 2018: Trade Logistics in the Global Economy - The Logistics Performance Index and Its Indicators: Connecting to Compete 2018 : Trade Logistics in the Global Economy - The Logistics Performance Index and Its Indicators (English)", World Bank Group, Washington, D.C.

Ayçin, E. (2020). "Personel Seçim Sürecinde CRITIC ve MAIRCA Yöntemlerinin Kullanılması", *İşletme,* 1(1), 1-12.

Azhigali, A.B. (2023). "Digitalization and Digital Literacy in Logistics: Preparedness of the Employees for a Digital Transformation", Doctoral dissertation. Åbo Akademi University, Åbo.

Bakan, İ. and Şekkeli, Z.H. (2017). "Lojistik Yönetimi", Seçkin Yayıncılık, Ankara.

Baker, D., Bridges, D., Hunter, R., Johnson, G., Krupa, J., Murphy, J. and Sorenson, K. (2002). "Guidebook to Decision Making Methods", WSRC-IM-2002-00002. Department of Energy, USA.

Bamyacı, M. (2008). "Modern Lojistik Yönetimi: Organize Lojistik Bölgeleri için Bir Yer Seçim Modeli", Unpublished PhD Thesis. İstanbul University Institute Of Graduate Studies In Sciences, İstanbul.

Barasin, A.M., Alqahtani, A.Y. and Makki, A.A. (2024). "Performance Evaluation of Retail Warehouses: A Combined MCDM Approach Using G-BWM and RATMI", *Logistics,* 8(1), 10. https://doi.org/10.3390/logistics8010010

Barilla, D., Carlucci, F., Cirà, A., Ioppolo, G. and Siviero, L. (2020). "Total Factor Logistics Productivity: A Spatial Approach to the ITALIAN Regions", *Transportation Research Part A: Policy and Practice,* 136*,* 205-222. https://doi.org/10.1016/j.tra.2020.03.033

Bayraktutan, Y. and Özbilgin, M. (2015). "Lojistik Maliyetler ve Lojistik Performans Ölçütleri", *Maliye Araştırmaları Dergisi,* 1(1), 95-112.

Beysenbaev, R. (2018). "The Importance of Country-Level Logistics Efficiency Assessment to the Development of International Trade", *British Journal for Social and Economic Research,* 3(6), 13-20. https://doi.org/10.22406/bjser-18-3.6-13-20

Candemir, Y. and Çelebi, D. (2017). "An Inquiry into the Analysis of the Transport & Logistics Sectors' Role in Economic Development", *Transportation Research Procedia,* 25*,* 4692-4707. https://doi.org/10.1016/j.trpro.2017.05.317

Chejarla, K.C., Vaidya, O.S. and Kumar, S. (2022). "MCDM Applications in Logistics Performance Evaluation: A Literature Review" *Journal of Multi-Criteria Decision Analysis,* 29(3-4), 274-297. https://doi.org/10.1002/mcda.1774

Chen, C.L. (2020). "Cross-Disciplinary Innovations by Taiwanese Manufacturing SMEs in the Context of Industry 4.0", *Journal of Manufacturing Technology Management,* 6(31), 1145-1168. https://doi.org/10.1108/JMTM-08-2019-0301

Cheng, S.P. and Peng, Q.Y. (2006). "Empirical Analysis on the Effect of Anhui Logistics Industry and Economic Development", *Jiatong Standardization,* 2, 186-189.

Choi, T.M. (2021). "Risk Analysis in Logistics Systems: A Research Agenda during and after the COVID-19 Pandemic", *Transportation Research Part E: Logistics and Transportation Review,* 145, 102190. https://doi.org/10.1016/j.tre.2020.102190

Chopra, S. and Sodhi, M.S. (2004). "Managing Risk to Avoid Supply-Chain Breakdown". *MIT Sloan Management Review*, 46(1), 53-61.

Chu, Z. (2012). "Logistics and Economic Growth: A Panel Data Approach", *The Annals of Regional Science,* 49(1), 87-102. https://doi.org/10.1007/s00168-010-0434-0

Clausen, U., De Bock, J. and Lu, M. (2016). "Logistics Trends, Challenges, and Needs for Further Research and Innovation", *Sustainable Logistics and Supply Chains: Innovations and Integral Approaches,* (Editors: M. Lu and J.D. Bock) , 1-13, Springer Cham. https://doi.org/10.1007/978-3-319-17419-8

Çalık, A., Erdebilli, B. and Özdemir, Y.S. (2023). "Novel Integrated Hybrid Multi-Criteria Decision-Making Approach for Logistics Performance Index", *Transportation Research Record,* 2677(2), 1392-1400. https://doi.org/10.1177/036119812211133

Çınaroğlu, E. (2020). "Yenilikçi Girişimlere Ait Faaliyetlerin ENTROPI Destekli MABAC Yöntemi İle Değerlendirilmesi", *Girişimcilik ve İnovasyon Yönetimi Dergisi,* 9(1), 111-135.

Demir, G. and Bircan, H. (2020). "Kriter Ağırlıklandırma Yöntemlerinden BWM ve FUCOM Yöntemlerinin Karşılaştırılması ve Bir Uygulama", *Sivas Cumhuriyet Üniversitesi İktisadi ve İdari Bilimler Dergisi,* 21(2), 170-185. https://doi.org/10.37880/cumuiibf.616766

Démurger, S. (2001). "Infrastructure Development and Economic Growth: An Explanation for Regional Disparities in China", *Journal of Comparative Economics*, 29(1), 95-117.

Ecer, F. and Aycin, E. (2023). "Novel Comprehensive MEREC Weighting-Based Score Aggregation Model for Measuring Innovation Performance: The Case of G7 Countries", *Informatica,* 34(1), 53-83. https://doi.org/10.15388/22-INFOR494

Eren, H. (2021). "MULTIMOORA Yöntemi İle Lojistik Sektöründe Faaliyet Gösteren Işletmelerin Performans Analizi", *International Başkent Congress on Physical, Social and Health Sciences,* 122-134.

Erkan, B. (2014). "Türkiye'de Lojistik Sektörü ve Rekabet Gücü", *ASSAM Uluslararası Hakemli Dergi,* 1(1), 44-65.

Ersoy, N. (2022). "OECD ve AB Üyesi Ülkelerin İnovasyon Performanslarının MEREC-MARCOS Bütünleşik Modeli İle Ölçümü", *Dokuz Eylül Üniversitesi Sosyal Bilimler Enstitüsü Dergisi,* 24(3), 1039-1063. https://doi.org/10.16953/deusosbil.1106249

Eskandaripour, H. and Boldsaikhan, E. (2023). "Last-Mile Drone Delivery: Past, Present, and Future", *Drones,* 7(2), 77. https://doi.org/10.3390/drones7020077

Esmeray, M. and Özveri, O. (2023). "Tedarikçi Seçiminde Farklı Çok Kriterli Karar Verme Yöntemlerinden Elde Edilen Sonuçların Karşılaştırılması", *Yaşar Üniversitesi E-Dergisi,* 18(72). 587-602. https://doi.org/10.19168/jyasar.1273595

Fan, L. (2019). "The Spatial-Temporal Analysis of the Green Total Factor Productivity of Logistics Industry in China", *16th International Conference on Service Systems and Service Management (ICSSSM).* 1-4.

Galan, N. and Torsein, E. (2021). "Identification of International Opportunities: A Study of Mature Firms in Mature Industries", *Journal of International Entrepreneurship,* 19, 53-103. https://doi.org/10.1007/s10843-020-00277-1

Gani, A. (2017). "The Logistics Performance Effect in International Trade", *The Asian Journal of Shipping and Logistics,* 33(4), 279-288. https://doi.org/10.1016/j.ajsl.2017.12.012

Gigović, L., Pamučar, D., Bajić, Z. and Milićević, M. (2016). "The Combination of Expert Judgment and GIS-MAIRCA Analysis for the Selection of Sites for Ammunition Depots", *Sustainability,* 8(4), 1-30. https://doi.org/10.3390/su8040372

Goel, R.K., Saunoris, J.W. and Goel, S.S. (2021). "Supply Chain Performance and Economic Growth: The Impact of COVID-19 Disruptions", *Journal of Policy Modeling,* 43(2), 298-316. https://doi.org/10.1016/j.jpolmod.2021.01.003

Gülenç, İ.F. and Karagöz, B. (2008). "E-lojistik ve Türkiye'de E-Lojistik Uygulamaları", *Kocaeli Üniversitesi Sosyal Bilimler Enstitüsü Dergisi,* 15, 73-91.

Gürler, H.E., Özçalıcı, M. and Pamucar, D. (2024). "Determining Criteria Weights with Genetic Algorithms for Multi-Criteria Decision Making Methods: The Case of Logistics Performance Index Rankings of European Union Countries", *Socio-Economic Planning Sciences,* 91, 101758. https://doi.org/10.1016/j.seps.2023.101758

Hayaloğlu, P. (2015). "The Impact of Developments in the Logistics Sector on Economic Growth: The Case of OECD Countries", *International Journal of Economics and Financial Issues,* 5(2), 523-530.

Işık, Ö. (2022). "Covid-19 Salgının Katılım Bankacılığı Sektörünün Performansına Etkisinin MEREC-PSI-MAIRCA Modeliyle Incelenmesi", *Nişantaşı Üniversitesi Sosyal Bilimler Dergisi,* 10(2), 363-385. https://doi.org/10.52122/nisantasisbd.1167829

Jusufbašić, A. (2023). "MCDM Methods for Selection of Handling Equipment in Logistics: A Brief Review", *Spectrum of Engineering and Management Sciences,* 1(1), 13-24. https://doi.org/10.31181/sems1120232j

Kailaku, S.I., Arkeman, Y., Purwanto, Y.A. and Udin, F. (2022). "Logistics Network Configuration: The Solution for Quality-Related Problems in long-Distance Transportation of Mango in Indonesia", *IOP Conference Series: Earth and Environmental Science,* 1063(1), 012057, IOP Publishing. https://doi.org/10.1088/1755-1315/1063/1/012057

Kara, K. (2022). "Relationship between Domestic Logistics Opportunity Effiency and International Logistics Opportunity Efficiency Based on Market Potential: Empirical Research on Developing Countries", *Journal of Management Marketing and Logistics,* 9(2), 79-89. https://doi.org/10.17261/Pressacademia.2022.1555

Kara, K., Bentyn, Z. and Yalçın, G.C. (2022). "Determining the Logistics Market Performance of Developing Countries by Entropy and MABAC Methods", *LogForum,* 18(4), 421-434. https://doi.org/10.17270/J.LOG.2022.752

Kara, M., Tayfur, L. and Basık, H. (2009). "Küresel Ticarette Lojistik Üsleri Önemi ve Türkiye", *Mustafa Kemal Üniversitesi Sosyal Bilimler Enstitüsü Dergisi,* 6(11), 69-84.

Kaya, S.K. (2020). "Evaluation of the Effect of COVID-19 on Countries' Sustainable Development Level: A Comparative MCDM Framework", *Operational Research in Engineering Sciences: Theory and Applications,* 3(3), 101-122. DOI:10.31181/oresta20303101k

Keshavarz-Ghorabaee, M., Amiri, M., Zavadskas, E.K., Turskis, Z. and Antucheviciene, J. (2021). "Determination of Objective Weights Using A New Method Based on the Removal Effects of Criteria (MEREC)", *Symmetry,* 13*(*4), 2-20. https://doi.org/10.3390/sym13040525

Khadim, Z., Batool, I., Akbar, A., Poulova, P. and Akbar, M. (2021). "Mapping the Moderating Role of Logistics Performance of Logistics Infrastructure on Economic Growth in Developing Countries", *Economies,* 9(4), 177. https://doi.org/10.3390/economies9040177

Khan, S.A.R., Jian, C., Zhang, Y., Golpîra, H., Kumar, A. and Sharif, A. (2019). "Environmental, Social and Economic Growth Indicators Spur Logistics Performance: From the Perspective of South Asian Association for Regional Cooperation Countries", *Journal of Cleaner Production,* 214*,* 1011-1023. https://doi.org/10.1016/j.jclepro.2018.12.322

Khanzode, A.G., Sarma, P.R.S., Mangla, S.K. and Yuan, H. (2021). "Modeling the Industry 4.0 Adoption for Sustainable Production in Micro, Small & Medium Enterprises", *Journal of Cleaner Production,* 279*,* 123489. https://doi.org/10.1016/j.jclepro.2020.123489

Kalischuк, E.L. and Nebelyuk, V.V. (2021). "Productivity of Logistics Business Processes in the Conditions of Sustainable Development of Economic Systems", *Repository of Brest State Technical University,* 2021(C*),* 209-214.

Korucuk, S. (2021). "Ordu ve Giresun Illerinde Kentsel Lojistik Performans Unsurlarina Yönelik Karşilaştirmali Bir Analiz", *Dicle Üniversitesi Sosyal Bilimler Enstitüsü Dergisi,* 26, 141-155.

Kuković, D., Topolšek, D., Rosi, B. and Jereb, B. (2014). "A Comparative Literature Analysis of Definitions for Logistics: Between General Definition and Definitions of Subcategories", *Business Logistics in Modern Management,* 14th International Scientific Conference - Osijek, Croatia.

Lai, K.H., Ngai, E.W.T. and Cheng, T.C.E. (2004). "An Empirical Study of Supply Chain Performance in Transport Logistics", *International Journal of Production Economics,* 87(3), 321-331. https://doi.org/10.1016/j.ijpe.2003.08.002

Lambert, D., Stock, J.R. and Ellram, L.M. (1998). "Fundamentals of Logistics Management", McGraw-Hill.

Lassnig, M., Müller, J. M., Klieber, K., Zeisler, A. and Schirl, M. (2022). "A Digital Readiness Check for the Evaluation of Supply Chain Aspects and Company Size for Industry 4.0", *Journal of Manufacturing Technology Management,* 33(9), 1-18. https://doi.org/10.1108/JMTM-10-2020-0382

Lean, H.H., Huang, W. and Hong, J. (2014). "Logistics and Economic Development: Experience from China", *Transport Policy, 32,* 96-104. https://doi.org/10.1016/j.tranpol.2014.01.003

Liang, Z., Chiu, Y.H., Li, X., Guo, Q. and Yun, Y. (2020). "Study on the Effect of Environmental Regulation on the Green Total Factor Productivity of Logistics Industry from the Perspective of Low Carbon", *Sustainability,* 12(1), 175. https://doi.org/10.3390/su12010175

Luyen, L.A. and Thanh, N.V. (2022). "Logistics Service Provider Evaluation and Selection: Hybrid SERVQUAL–FAHP–TOPSIS Model", *Processes,* 10(5), 1024. https://doi.org/10.3390/pr10051024

Majerčák, P., Masárová, G., Buc, D. and Majerčáková, E. (2013). "System Approach of Logistic Costs Optimization Solution in Supply Chain", *NAŠE MORE: znanstveni časopis za more i pomorstvo,* 60(5-6), 95-98.

Martyn, K. and Kadzinski, M. (2023). "Deep Prefence Learning for Multiple Criteria Decision Analysis", *European Journal of Operational Research,* 305(2), 781-805. https://doi.org/10.1016/j.ejor.2022.06.053

Masood, T. and Sonntag, P. (2020). "Industry 4.0: Adoption Challenges and Benefits for SMEs", *Computers in Industry,* 121*,* 103261. https://doi.org/10.1016/j.compind.2020.103261

Mešić, A., Miškić, S., Stević, Ž. and Mastilo, Z. (2022). "Hybrid MCDM Solutions for Evaluation of the Logistics Performance Index of the Western Balkan Countries", *Economics,* 10(1), 13-34. https://doi.org/10.2478/eoik20220004

Milosavljević, M., Bursać, M. and Tričković, G. (2018). "Selection of the Railroad Container Terminal in Serbia Based on Multi Criteria Decision Making Methods", *Decision Making: Applications in Management and Engineering,* 1(2), 1-15. https://doi.org/10.31181/dmame1802001m

Mino, P. and Austin, L. (2022). "A Cocreational Approach to Nation Branding: The Case of Chile", *Public Relations Inquiry*, 11(2), 293-313. https://doi.org/10.1177/2046147X221081179

Miškić, S., Stević, Ž., Tadić, S., Alkhayyat, A. and Krstić, M. (2023). "Assessment of the LPI of the EU Countries Using MCDM Model with An Emphasis on the Importance of Criteria", *World Review of Intermodal Transportation Research,* 11(3), 258-279. https://doi.org/10.1504/WRITR.2023.132501

Montoya-Torres, J.R., Muñoz-Villamizar, A. and Mejia-Argueta, C. (2023). "Mapping Research in Logistics and Supply Chain Management during COVID-19 Pandemic", *International Journal of Logistics Research and Applications,* 26(4), 421-441. https://doi.org/10.1080/13675567.2021.1958768

Nekhoroshkov, V., Aroshidze, A., Majercak, P. and Kurenkov, P. (2021). "Features of Logistics Development in the BRICS Countries", *SHS Web of Conferences,* EDP Sciences.

Nguyen, N.A.T., Wang, C.N., Dang, L.T.H., Dang, L.T.T. and Dang, T.T. (2022). "Selection of Cold Chain Logistics Service Providers Based on a Grey AHP and Grey COPRAS Framework: A Case Study in Vietnam", *Axioms,* 11(4), 154. https://doi.org/10.3390/axioms11040154

Noyan, E. (2023). "Banka Personeli Seçiminin Çok Kriterli Karar Verme Yöntemleri Ile Ele Alınması", *Kapanaltı Dergisi,* 4. 112-121.

Nurprihatin, F., Regina, T. and Rembulan, G.D. (2021). "Optimizing Rice Distribution Routes in Indonesia Using A Two-Step Linear Programming Considering Logistics Costs", *Journal of Physics: Conference Series*, 1811(1), 012010. https://doi.org/10.1088/1742-6596/1811/1/012010

Ohh, W.G. (2012). "Analysis on Productivity of Logistics Providers Focusing on the Warehouses Industry", *Journal of Korea Port Economic Association,* 28(2), 113-128.

Opricovic, S. and Tzeng, G. (2004). "Compromise Solution by MCDM Methods: A Comparative Analysis of VIKOR and TOPSIS", *European Journal of Operational Research,* 156*,* 445-455. https://doi.org/10.1016/S0377-2217(03)00020-1

Özbek, H.E. and Özekenci, E.K (2023). "Investigation of Digital Logistics Market Performance in Developing Countries with Hybrid MCDM Methods", *Journal of Emerging Economies and Policy,* 8(2), 559-576.

Özçalıcı, M. (2022). "Asset Allocation with Multi-Criteria Decision Making Techniques", *Decision Making: Applications in Management and Engineering,* 5(2), 78-119. https://doi.org/10.31181/dmame0305102022o

Özdağoğlu, A., Ulutaş, A. and Keleş, M.K. (2022). "Lojistik Değerlendirme Ölçütlerine göre Ülke Sıralamaları: Farklı Yöntemlerin Sıralama Üzerindeki Etkisi", *Journal of Mehmet Akif Ersoy University Economics and Administrative Sciences Faculty, 9*(1), 512-541. https://doi.org/10.30798/makuiibf.913369

Özekenci, E.K. (2023). "Assessing the Logistics Market Performance of Developing Countries by SWARA-CRITIC based CoCoSo Methods", *LogForum,* 19(3), 375-394. https://doi.org/10.17270/J.LOG.2023.857

Pala, O. (2023). "MEREC-CORR ve SAW Temelli Lojistik Performans Değerlendirme", *Dicle Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi,* 13(25), 117-135. https://doi.org/10.53092/duiibfd.1130928

Pamućar, D. and Ćirović, G. (2015). "The Selection of Transport and Handling Resources in Logistics Centers Using Multi-Attributive Border Approximation Area Comparison (MABAC)", *Expert Systems with Applications,* 42(6), 3016-3028. https://doi.org/10.1016/j.eswa.2014.11.057

Pamučar, D., Mihajlović, M., Obradović, R. and Atanasković, P. (2017). "Novel Approach to Group Multicriteria Decision Making Based on Interval Rough Numbers: Hybrid DEMATEL-ANP-MAIRCA Model", *Expert Systems with Applications,* 88, 58-80. https://doi.org/10.1016/j.eswa.2017.06.037

Pamucar, D.S., Tarle, S.P. and Parezanovic, T. (2018). "New Hybrid Multi-Criteria Decision-Making DEMATEL-MAIRCA Model: Sustainable Selection of A Location for the Development of Multimodal Logistics Centre", *Economic Research-Ekonomska Istraživanja,* 31(1), 1641-1665. https://doi.org/10.1080/1331677X.2018.1506706

Patella, S.M., Grazieschi, G., Gatta, V., Marcucci, E. and Carrese, S. (2021). "The Adoption of Green Vehicles in Last Mile Logistics: A Systematic Review", *Sustainability,* 13(1), 6. https://doi.org/10.3390/su13010006

Pehlivan, N.Y. (2024). “A Novel Integrated FCM/MCDM Methodology for Evaluating Logistic Performance Index”, *Data-Driven Modelling with Fuzzy Sets*, 305-328. CRC Press.

Pfohl, H.C. (2022). “Logistics Systems”, Springer, Berlin Heidelberg.

Pfohl, H.C. (2023). “Logistics as A Success Factor”. *Logistics Management,* Springer, Berlin Heidelberg. https://doi.org/10.1007/978-3-662-66564-0_3

Pham, T.H. and Doan, T.D.U. (2020). “Supply Chain Relationship Quality, Environmental Uncertainty, Supply Chain Performance and Financial Performance of High-Tech Agribusinesses in Vietnam”, *Uncertain Supply Chain Management,* 8, 663-674. https://doi.org/10.5267/j.uscm.2020.8.006

Popescu, A. and Sipos, C. (2014). “Logistics Performance and Economic Development-A Comparison within the European Union”, *Proceedings of “MAC-EMM”,* Prague, Czech Republic.

Pradhan, R.P.I. and Bagchi, T.P. (2013). “Effect of Transportation Infrastructure on Economic Growth in India: The VECM Approach”, *Research in Transportation Economics,* 38(1), 139-148.

Rezaei, J., van Roekel, W.S. and Tavasszy, L. (2018). “Measuring the Relative Importance of the Logistics Performance Index Indicators Using Best Worst Method”, *Transport Policy,* 68, 158-169. https://doi.org/10.1016/j.tranpol.2018.05.007

Rokicki, T., Bórawski, P., Bełdycka-Bórawska, A., Szeberényi, A., and Perkowska, A. (2022). “Changes in Logistics Activities in Poland as A Result the COVID-19 Pandemic”, *Sustainability,* 14(16), 10303. https://doi.org/10.3390/su141610303

Rostek, M. (2022). “Productivity and Improvement of Logistics Processes in the Company Manufacturing Vehicle Semi-Trailers Case Study”, *Production Engineering Archives,* 28(4), 309-318. https://doi.org/10.30657/pea.2022.28.39

Salvatore, D. (2020). “Growth and Trade in the United States and the World Economy: Overview”, *Journal of Policy Modeling,* 42(4), 750-759. https://doi.org/10.1016/j.jpolmod.2020.03.001

Savytska N., Zhehus O., Chmil H., Uchakova N., Androsova T. and Priadko O. (2022). “Applied Research of Digital Readiness of Retails”, *WSEAS Transactions on Environment and Development,* 18, 798-809.

Sawant, P.B. (2013). “Analysis of Logistics Infrastructure in India”, Doctoral Dissertation, University of Mumbai, India.

Sereda, A.E. (2021). “Digitalization of Logistics Processes as A Factor of Enhancing Productivity of Logistics”, *Стратегии и Инструменты Управления Экономикой: Отраслевой и Региональный Аспект,*138-142.

Shanmugasundar, G., Sapkota, G., Čep, R. and Kalita, K. (2022). “Application of MEREC in Multi-Criteria Selection of Optimal Spray-Painting Robot”, *Processes,* 10(6), 1172. https://doi.org/10.3390/pr10061172

Shikur, Z.H. (2022). “Logistics Performance, Export, Agricultural, Manufacturing, and Aggregate Economic Growth: A Focus on Sectoral Perspectives”, *Journal of Economic Development,* 47(3), 107-123.

Singh, M. and Pant, M. (2021). “A Review of Selected Weighing Methods in MCDM with A Case Study”, *International Journal of System Assurance Engineering and Management,* 12, 126-144. https://doi.org/10.1007/s13198-020-01033-3

Somohano-Rodríguez, F.M., Madrid-Guijarro, A. and López-Fernández, J.M. (2022). “Does Industry 4.0 Really Matter for SME Innovation”, *Journal of Small Business Management,* 60(4), 1001-1028. https://doi.org/10.1080/00472778.2020.1780728

Stainer, A. (1997). “Logistics-A Productivity and Performance Perspective”, *Supply Chain Management: An International Journal,* 2(2), 53-62. https://doi.org/10.1108/13598549710166104

Stević, Ž., Tanackov, I., Puška, A., Jovanov, G., Vasiljević, J. and Lojaničić, D. (2021). “Development of Modified SERVQUAL–MCDM Model for Quality Determination in Reverse Logistics”, *Sustainability,* 13(10), 5734. https://doi.org/10.3390/su13105734

Štimac, H., Freimann, A. and Glavaš, J. (2021). “Logistical Challenges in the Process of Internationalization of Companies in the Wine Industry”, *21st International Scientific Conference Business Logistics in Modern Management (BLMM 2021),* 245-258.

T.C. Dış İşleri Bakanlığı. (2023). “Dış Politika, Bölgeler, Latin Amerika Şili’nin Ekonomisi.” https://www.mfa.gov.tr/sili-ekonomisi.tr.mfa, (Accessed Date: 01.07.2023).

The World Bank (2018). “Connecting to compete 2018: Trade Logistics in the Global Economy”. https://openknowledge.worldbank.org/bitstream/handle/10986/29971/LPI2018.pdf, (Accessed Date: 09.07.2024).

Tian, G., Lu, W., Zhang, X., Zhan, M., Dulebenets, M.A., Aleksandrov, A., Fathollahi-Fard, A.M. and Ivanov, M. (2023). “A Survey of Multi-Criteria Decision-Making Techniques for Green Logistics and Low-Carbon Transportation Systems”, *Environmental Science and Pollution Research,* 30(20), 57279-57301. https://doi.org/10.1007/s11356-023-26577-2

Tomassian, G.C., Perrotti, D. and Sánchez, R. (2014). “Desarrollo Económico y Desempeño Logístico. Un Enfoque Probabilístico”, *Revista de Economía Mundial,* 38, 27-48.

Top, M. and Bulut, T. (2022). "Yeni Bir Çok Kriterli Karar Verme Yöntemi: Bulut Endeks- Beta (BE-β)", *Verimlilik Dergisi,* 3*,* 393-414. https://doi.org/10.51551/verimlilik.1031366

Torkayesh, A.E., Tirkolaee, E.B., Bahrini, A., Pamucar, D. and Khakbaz, A. (2023). "A Systematic Literature Review of MABAC Method and Applications: An Outlook for Sustainability and Circularity", *Informatica,* 34(2), 415-448. https://doi.org/10.15388/23-INFOR511

Trung, D.D. and Thinh, H.X. (2021). "A Multi-Criteria Decision-Making in Turning Process Using the MAIRCA, EAMR, MARCOS and TOPSIS Methods: A Comparative Study", *Advances in Production Engineering & Management,* 16(4), 443-456. https://doi.org/10.14743/apem2021.4.412

Ulutaş, A. and Karaköy, Ç. (2019). "An Analysis of the Logistics Performance Index of EU Countries with An Integrated MCDM Model", *Economics and Business Review,* 5(4), 49-69.

Ulutaş, A. and Karaköy, Ç. (2021). "Evaluation of LPI Values of Transition Economies Countries with A Grey MCDM Model", *Handbook of Research on Applied AI for International Business and Marketing Applications,* 499-511. IGI Global. https://doi.org/10.4018/978-1-7998-5077-9.ch024

Wang, M. (2018). "Impacts of Supply Chain Uncertainty and Risk on the Logistics Performance", *Asia Pacific Journal of Marketing and Logistics,* 30(3), 689-704. https://doi.org/10.1108/APJML-04-2017-0065

Widodo, K.H., Parikesit, D., Purwoto, H., Soemardjito, J. and Eriadi. (2018). "Issues and Challenges in URBAN Logistics Planning in Indonesia", *City Logistics 3: Towards Sustainable and Liveable Cities*, 317-327. https://doi.org/10.1002/9781119425472.ch18

Wilson, M.C. (2007). "The Impact of Transportation Disruptions on Supply Chain Performance", *Transportation Research Part E: Logistics and Transportation Review,* 43(4), 295-320. https://doi.org/10.1016/j.tre.2005.09.008

Wong, W.P. and Tang, C.F. (2018). "The Major Determinants of Logistic Performance in A Global Perspective: Evidence from Panel Data Analysis", *International Journal of Logistics Research and Applications,* 21(4), 431-443. https://doi.org/10.1080/13675567.2018.1438377

Xu, F., Song, Y. and Hu, H. (2012). "Application of Cycle-Based Simulation to Estimate Loss of Logistics Productivity on Construction Sites", *Computational Logistics: Third International Conference, ICCL 2012,* Shanghai, China, September 24-26, 2012, Springer, Berlin Heidelberg. https://doi.org/10.1007/978-3-642-33587-7_12

Xu, X. and Wang, Y. (2017). "Study on Spatial Spillover Effects of Logistics Industry Development for Economic Growth in the Yangtze River Delta City Cluster Based on Spatial Durbin Model", *International Journal of Environmental Research and Public Health,* 14(12), 1508. https://doi.org/10.3390/ijerph14121508

Yalçın, B. and Ayvaz, B. (2020). "Çok Kriterli Karar Verme Teknikleri Ile Lojistik Performansın Değerlendirilmesi", *İstanbul Ticaret Üniversitesi Fen Bilimleri Dergisi,* 19(38), 117-138.

Zhang, X., Lu, J. and Peng, Y. (2021). "Hybrid MCDM Model for Location of Logistics Hub: A Case in China under the Belt and Road Initiative", *IEEE Access,* 9*,* 41227-41245. https://doi.org/10.1109/ACCESS.2021.3065100

APPENDIX

Table A1. Abbreviations used in the study and their explanations.

Abbreviations	*Explanations*	*Abbreviations*	*Explanations*
AEMLI	Agility Emerging Markets Logistics Index	KWT	State of Kuwait
ARAS	Additive Ratio Assessment	LOPCOW	Logarithmic Percentage Change-Driven Objective Weighting
ASEAN	Association of Southeast Asian Nations	LPI	Logistics Performance Index
BF	Business Fundametals	MARCOS	Measurement of Alternatives and Ranking according to Compromise Solution
BHR	Kingdom of Bahrain	MCDM	Multi-Criteria Decision Making
BRA	Federative Republic of Brazil	MABAC	Multi Attributive Border Approximation Area Comparison
CHL	Republic of Chile	MAIRCA	Multi-Attributive Ideal-Real Comparative Analysis
CHN	People's Republic of China	MAUT	Multi-Attribute Utility Theory
CKPI	Customer-oriented Key Performance Indicators	MEREC	Method Based on the Removal Effects of Criteria
CoCoSo	Combined Compromise Solution	MEX	United Mexican States
CODAS	Combinative Distance-Based Assessment	MOORA	Multi-Objective Optimization by Ratio Analysis
COPRAS	Complex Proportional Assessment	MYS	Malaysia
CRITIC	Criteria Importance Through Intercriteria Correlation	OMN	Sultanate of Oman
DO	Domestic Opportunities	PSI	Preference Selection Index
DR	Digital Readiness	QAT	State of Qatar
ELECTRE	ELimination Et Choix Traduisant la Realite	RATMI	Ranking the Alternatives Based on the Trace to Median Index
EU	The European Union	RUS	Russian Federation
FCM F-TOPSIS	Fuzzy Technique for Order Preference by Similarity to Ideal Solution	SAM	Similarity Aggregation Method
FAHP	Fuzzy Analytic Hierarchy Process	SAU	Kingdom of Saudi Arabia
FCM	Fuzzy C-Means	SAW	Simple Additive Weighting
FUCOM	Full Consistency Method	SD	Standard Deviation
G-BWM	Generalized Best Worst Method	SERVQUAL	Service Quality
G-MOORA	Generalized Multi-Objective Optimization by Ratio Analysis	THA	Kingdom of Thailand
G-SWARA	Generalized Step-Wise Weight Assessment Ratio Analysis	TUR	Republic of Türkiye
GRA	Grey Relational Analysis	UAE	United Arab Emirates
IDN	Republic of Indonesia	VNM	Socialist Republic of Vietnam
IND	Republic of India	WASPAS	Weighted Aggregated Sum Product Assessment
IO	International Opportunities	WPM	Weighted Product Method
JOR	Hashemite Kingdom of Jordan	WSM	Weighted Sum Method

Table A2. Normalization matrix (2022) (MEREC)

Alternatives	*DO*	*IO*	*BF*	*DR*
CHN	0.5702	0.4759	0.6934	0.7707
IND	0.6007	0.6228	0.8300	0.6715
UAE	0.8625	0.7878	0.5418	0.6934
MYS	0.9130	0.7891	0.6280	0.7604
IDN	0.7618	0.7878	0.8544	0.8229
SAU	0.8978	0.8084	0.6272	0.8111
QAT	0.8173	0.9355	0.6225	0.8009
THA	0.9452	0.7759	0.8544	0.8460
MEX	0.8994	0.7342	1.0000	1.0000
TUR	0.9397	0.8140	0.8500	0.9291
VNM	0.9622	0.7695	0.8788	0.9411
CHL	1.0000	0.8958	0.7073	0.9207
KWT	0.9527	1.0000	0.7913	0.8872
OMN	0.9758	0.9508	0.6809	0.8795
BHR	0.9679	0.9872	0.6895	0.9569

Table A3. Normalization matrix (2023) (MEREC)

Alternatives	*DO*	*IO*	*BF*	*DR*
CHN	0.5632	0.5055	0.6274	0.6394
IND	0.6120	0.6039	0.6630	0.8217
UAE	0.8714	0.7525	0.4834	0.7500
MYS	0.9162	0.7612	0.5370	0.7878
IDN	0.7599	0.7240	0.6936	0.9053
SAU	0.8891	0.7512	0.5783	0.8571
QAT	0.8409	0.9310	0.5839	0.8113
THA	0.9376	0.7701	0.7641	0.8790
MEX	0.8957	0.7344	0.7782	1.0000
TUR	0.9179	0.8361	0.7531	0.9181
VNM	0.9144	0.7127	0.6982	0.9923
CHL	1.0000	0.8913	0.6066	0.9451
RUS	0.9544	0.8167	0.8143	0.9331
BRA	0.8810	0.7983	1.0000	0.9904
JOR	0.9938	1.0000	0.6058	0.9829

Table A4. Normalization matrix for MABAC (2022)

Alternatives	*DO*	*IO*	*BF*	*DR*
CHN	1.0000	1.0000	0.5228	0.6080
IND	0.8819	0.5499	0.2422	1.0000
UAE	0.2115	0.2446	1.0000	0.9040
MYS	0.1264	0.2427	0.7002	0.6440
IDN	0.4148	0.2446	0.2014	0.4400
SAU	0.1511	0.2153	0.7026	0.4760
QAT	0.2967	0.0626	0.7170	0.5080
THA	0.0769	0.2622	0.2014	0.3720
MEX	0.1484	0.3288	0.0000	0.0000
TUR	0.0852	0.2074	0.2086	0.1560
VNM	0.0522	0.2720	0.1631	0.1280
CHL	0.0000	0.1057	0.4988	0.1760
KWT	0.0659	0.0000	0.3118	0.2600
OMN	0.0330	0.0470	0.5540	0.2800
BHR	0.0440	0.0117	0.5324	0.0920

Table A5. Normalization matrix for MABAC (2023)

Alternatives	*DO*	*IO*	*BF*	*DR*
CHN	1.0000	1.0000	0.5556	1.0000
IND	0.8177	0.6704	0.4756	0.3849
UAE	0.1903	0.3363	1.0000	0.5911
MYS	0.1180	0.3207	0.8067	0.4777
IDN	0.4075	0.3898	0.4133	0.1856
SAU	0.1609	0.3385	0.6822	0.2955
QAT	0.2444	0.0757	0.6667	0.4124
THA	0.0858	0.3051	0.2889	0.2440
MEX	0.1501	0.3697	0.2667	0.0000
TUR	0.1153	0.2004	0.3067	0.1581
VNM	0.1206	0.4120	0.4044	0.0137
CHL	0.0000	0.1247	0.6067	0.1031
RUS	0.0617	0.2294	0.2133	0.1271
JOR	0.0080	0.0000	0.6089	0.0309
BRA	0.1743	0.2584	0.0000	0.0172

Table A6. Calculating the real evaluation matrix for MAIRCA (2022)

Alternatives	*DO*	*IO*	*BF*	*DR*
CHN	0.0113	0.0177	0.0127	0.0081
IND	0.0100	0.0097	0.0059	0.0134
UAE	0.0024	0.0043	0.0243	0.0121
MYS	0.0014	0.0043	0.0170	0.0086
IDN	0.0047	0.0043	0.0049	0.0059
SAU	0.0017	0.0038	0.0171	0.0064
QAT	0.0034	0.0011	0.0174	0.0068
THA	0.0009	0.0046	0.0049	0.0050
MEX	0.0017	0.0058	0.0000	0.0000
TUR	0.0010	0.0037	0.0051	0.0021
VNM	0.0006	0.0048	0.0040	0.0017
CHL	0.0000	0.0019	0.0121	0.0024
KWT	0.0007	0.0000	0.0076	0.0035
OMN	0.0004	0.0008	0.0135	0.0037
BHR	0.0005	0.0002	0.0129	0.0012

Table A7. Calculating the real evaluation matrix for MAIRCA (2023)

Alternatives	*DO*	*IO*	*BF*	*DR*
CHN	0.0105	0.0186	0.0159	0.0088
IND	0.0086	0.0125	0.0136	0.0034
UAE	0.0020	0.0063	0.0287	0.0052
MYS	0.0012	0.0060	0.0231	0.0042
IDN	0.0043	0.0073	0.0119	0.0016
SAU	0.0017	0.0063	0.0196	0.0026
QAT	0.0026	0.0014	0.0191	0.0036
THA	0.0009	0.0057	0.0083	0.0021
MEX	0.0016	0.0069	0.0076	0.0000
TUR	0.0012	0.0037	0.0088	0.0014
VNM	0.0013	0.0077	0.0116	0.0001
CHL	0.0000	0.0023	0.0174	0.0009
RUS	0.0006	0.0043	0.0061	0.0011
JOR	0.0001	0.0000	0.0175	0.0003
BRA	0.0018	0.0048	0.0000	0.0002

Table A8. Calculating the total gap matrix for MAIRCA (2022)

Alternatives	*DO*	*IO*	*BF*	*DR*
CHN	0.0000	0.0000	0.0116	0.0052
IND	0.0013	0.0080	0.0184	0.0000
UAE	0.0089	0.0134	0.0000	0.0013
MYS	0.0099	0.0134	0.0073	0.0048
IDN	0.0066	0.0134	0.0194	0.0075
SAU	0.0096	0.0139	0.0072	0.0070
QAT	0.0080	0.0166	0.0069	0.0066
THA	0.0104	0.0131	0.0194	0.0084
MEX	0.0096	0.0119	0.0243	0.0134
TUR	0.0103	0.0140	0.0192	0.0113
VNM	0.0107	0.0129	0.0203	0.0116
CHL	0.0113	0.0158	0.0122	0.0110
KWT	0.0106	0.0177	0.0167	0.0099
OMN	0.0109	0.0169	0.0108	0.0096
BHR	0.0108	0.0175	0.0114	0.0121

Table A9. Calculating the total gap matrix for MAIRCA (2023)

Alternatives	*DO*	*IO*	*BF*	*DR*
CHN	0.0000	0.0000	0.0127	0.0000
IND	0.0019	0.0061	0.0150	0.0054
UAE	0.0085	0.0124	0.0000	0.0036
MYS	0.0093	0.0127	0.0055	0.0046
IDN	0.0062	0.0114	0.0168	0.0072
SAU	0.0088	0.0123	0.0091	0.0062
QAT	0.0080	0.0172	0.0096	0.0052
THA	0.0096	0.0130	0.0204	0.0067
MEX	0.0090	0.0117	0.0210	0.0088
TUR	0.0093	0.0149	0.0199	0.0074
VNM	0.0093	0.0110	0.0171	0.0087
CHL	0.0105	0.0163	0.0113	0.0079
RUS	0.0099	0.0144	0.0226	0.0077
JOR	0.0105	0.0186	0.0112	0.0085
BRA	0.0087	0.0138	0.0287	0.0087

VERİMLİLİK DERGİSİ
JOURNAL OF PRODUCTIVITY

Evaluation of Barriers to Digital Transformation in Maritime Logistics Based on A Spherical Fuzzy Multi-Criteria Decision-Making Framework

Veysel Tatar[1]

ABSTRACT
Purpose: The objective of this study is to identify and prioritize the barriers to the adoption of digital transformation in order to ensure more efficient and effective operation of the maritime logistics sector.
***Methodology*:** The Spherical Fuzzy Analytical Hierarchy Process (SF-AHP) method, which gives successful results in modelling uncertainty and uses Spherical fuzzy sets (SFSs), is used to rank the barriers affecting adoption of digital transformation according to their importance.
Findings: In the application part of the study, firstly the barriers in the adoption of digital transformation were determined and as a result of expert evaluations, the barriers were ranked according to their importance by applying the steps of the method. When the results obtained from the study were examined, 'Technology' is the most important barrier category (B1) (0.341) for the adoption of digital transformation in maritime logistics, followed by the main barrier categories related to "Security" (B4) (0.266), "Environment" (B3) (0.223) and "Organisation" (B2) (0.171) respectively.
Originality: This study represents a pioneering effort in the field of maritime logistics, as it is the first to identify and prioritize the barriers to digital transformation that impede operational efficiency.
Keywords*:* Digital Transformation, Barrier, Spherical Fuzzy Set, AHP.
JEL Codes: D81, L91, O31.

Küresel Bulanık Çok Kriterli Karar Verme Çerçevesine Dayalı Olarak Denizcilik Lojistiğinde Dijital Dönüşümün Önündeki Engellerin Değerlendirilmesi

ÖZET
Amaç: Bu çalışmanın amacı, deniz lojistik sektörünün daha verimli ve etkin çalışmasını sağlamak için dijital dönüşümün benimsenmesinin önündeki engelleri tespit etmek ve önceliklendirmektir.
***Yöntem*:** Belirsizliğin modellenmesinde başarılı sonuçlar veren ve küresel bulanık kümeleri kullanan Küresel Bulanık Analitik Hiyerarşi Süreci (SF-AHP) yöntemi, dijital dönüşümün benimsenmesini etkileyen engelleri önem derecelerine göre sıralamak için kullanılmıştır.
Bulgular: Çalışmanın uygulama kısmında öncelikle dijital dönüşümün benimsenmesindeki engeller belirlenmiş ve uzman değerlendirmeleri sonucunda yöntemin adımları uygulanarak engeller önem derecelerine göre sıralanmıştır. Çalışmadan elde edilen sonuçlar incelendiğinde, deniz lojistiğinde dijital dönüşümün benimsenmesi için en önemli engel kategorisinin (B1) (0,341) 'Teknoloji' olduğu, bunu sırasıyla "Güvenlik" (B4) (0,266), "Çevre" (B3) (0,223) ve "Organizasyon" (B2) (0,171) ile ilgili ana engel kategorilerinin takip ettiği görülmüştür.
Özgünlük: Bu çalışma, operasyonel verimliliği engelleyen dijital dönüşümün önündeki engelleri tespit edip önceliklendirmesi bakımından deniz lojistiği alanında öncü bir çabayı temsil etmektedir.
Anahtar Kelimeler*:* Dijital Dönüşüm, Bariyer, Küresel Bulanık Küme, AHP.
JEL Kodları: D81, L91, O31.

[1] Artvin Çoruh University, Hopa Vocational School, Department of Maritime and Port Management, Artvin, Türkiye

Corresponding Author: Veysel Tatar, vtatar@artvin.edu.tr
DOI: 10.51551/verimlilik.1526042
Research Article | Submitted: 01.08.2024 | Accepted: 26.09.2024
Cite: Tatar, V. (2025). "Evaluation of Barriers to Digital Transformation in Maritime Logistics Based on A Spherical Fuzzy Multi-Criteria Decision-Making Framework", *Verimlilik Dergisi,* Productivity for Logistics (SI), 29-44.

1. INTRODUCTION

The digital century has recently changed the competitive dynamics of many businesses, including the logistics sector (Raza et al., 2023). Sustainable and efficient maritime transportation is essential to the world economy's continuous growth (Vujičić et al., 2020). The implementation of digital transformation has the potential to yield benefits for the maritime transport chain, such as enhanced business operations, reduced environmental impacts, and optimized cargo management (Jović et al., 2022). Digital transformation (DT) innovates the processes of traditional business models, providing opportunities for visibility and transparency, operational efficiency and integration and collaboration (Kache and Seuring, 2017; Tijan et al., 2021).

The global logistics industry, which had a market size of approximately 9.41 trillion US dollars in 2023, is expected to exceed 14.08 trillion U.S dollars by 2028 (Statista, 2024). Despite the rising costs of logistics, the sector is not adequately addressing the challenges of digitalisation in terms of sustainability (Parhi et al., 2022). Maritime logistics is a complex system that encompasses many interrelated factors. Therefore, the maritime industry, which deals with a large number of documents and procedures, needs the implementation of DT in the context of faster, more efficient and lower costs, operationally and commercially (Yang, 2019). The implementation of digital transformation in maritime companies, which encompasses concepts such as "Artificial Intelligence", "Internet of Things", "Cloud Computing", "Blockchain" and "Cybersecurity" related to Industry 4.0, will be important indicators in terms of customer satisfaction, environmental protection, cost efficiency, improved service quality and operational efficiency (Ichimura et al., 2022).

Maritime logistics, which integrates the global supply chain concept into maritime transportation, is an indispensable part of the global economy. In a competitive environment, shipping companies focus on key performance indicators ─ such as quality, speed, reliability, flexibility and cost (Panayides and Song, 2013). Digital technologies will enable more efficient operations in ports by shortening ship docking and waiting times at the terminal. In addition, it will reduce energy consumption and greenhouse gas emissions by optimizing ship arrival times by providing up-to-date meteorological information to the ship crew (Fruth and Teuteberg, 2017). The success of digital transformation in maritime logistics depends not only on the adoption of modern technologies but also on the cooperation of other stakeholders in the maritime transportation ecosystem (Heilig et al., 2017). Maritime logistics, which is important in terms of sea and land connection, is of great importance for maritime enterprises to use digital transformation in their business models in order to achieve sustainable goals and use their resources efficiently (Del Giudice et al., 2022). The maritime industry is undergoing a period of transition in order to adapt to the challenges of digital transformation. This transformation is focused on optimising cargo handling, streamline maritime procurement and logistics processes, enhancing efficiency, safety and reduce environmental effect (Babica et al., 2020).

The Analytical Hierarchy Process (AHP) is a frequently employed multi-criteria decision-making methodology, devised by Saaty (1977), for addressing intricate decision-making challenges (Kumar and Pant, 2023). It is a systematic approach to the prioritisation, ranking and evaluation of criteria and sub-criteria in accordance with the main goal. The traditional AHP approach is insufficient for addressing the absence of information or ambiguity in decision-maker (DM) judgments (Özkan et al., 2022). To address this limitation, the spherical fuzzy set (SFS) theory proposed Kahraman and Kutlu Gündoğdu (2018) is integrated into the AHP framework. The SFS methodology entails the definition of a fuzzy membership function on a spherical surface, accompanied by the independent assignment of function inputs to a larger domain. This approach affords decision-makers the flexibility to express ambivalence during the evaluation process (Dogan, 2021; Kutlu Gündoğdu and Kahraman, 2020a).

The current research study aims to address the above academic area and provide guidance to maritime industry managers by identifying and prioritising the potential barriers to the implementation of digital transformation practices by using the spherical fuzzy AHP (Kutlu Gündoğdu and Kahraman, 2020b) approach within the scope of the relevant literature review. In this context, the contributions of this study are as follows:

(1) This study identifies and constructs a hierarchical structure of the barriers to the adoption of DT in the maritime logistics sector, based on a comprehensive literature review.

(2) The proposal of a set of valid barriers to the implementation of digitalization in maritime logistics from the perspective of key stakeholders.

(3) To the best of the author's knowledge, this is the first study to utilize the AHP method based on SFS to evaluate the barriers in the digital transformation process in the maritime logistics sector. The spherical fuzzy AHP method was utilized to the determination of the relative importance of the criteria.

(4) In order to aggregate the judgement data of individual experts, a method based on the SWAM operator is employed to generate an aggregate evaluation matrix.

(5) The proposed approach will serve as a reference for experts and practitioners in the maritime logistics sector, offering crucial insights for the implementation of DT technologies.

(6) A comparative analysis was conducted to ascertain the robustness and applicability of the proposed methodology.

The rest of the manuscript is organized as follows: In Section 2, the barriers to adopting digital transformation are reviewed. Section 3 includes the introductory definitions and preliminary information on SFS and AHP methodology. Section 4 employs SF-AHP method to an illustration of an application. Subsequently, a comparative analysis is conducted in Section 4.1, while managerial implications are presented in Section 4.2. Finally, conclusions in Section 5.

2. LITERATURE REVIEW

The term "digitalization" is a key factor in the creation of new business models that aim to enhance business productivity and sustainability through the utilization of digital technologies within businesses (Ahmad et al., 2021; Jović et al., 2022). Fruth and Teuteberg (2017) emphasized reducing costs and protecting the environment by optimizing fleet controls with Big Data and digital transformation. Kechagias et al. (2022) highlighted that the maritime industry faces cyber risks with the increase in technological developments. Ahmad et al. (2021) posited that blockchain technology can be employed to effect the permanent and transparent recording of changes in the ownership or movements of shipments, cranes, and internal logistics vehicles. Port call optimization with the aid of digitalization is one of the crucial short-term steps that can considerably lower the CO_2 emissions of maritime transportation in the framework of international efforts towards the decarbonization of shipping (UNCTAD, 2020). Blockchain technologies facilitate safe and secure communication amongst supply chain participants in addition to enabling quick and dependable engagement within a broader network (Wei et al., 2019: 235). The maritime industry's quick adoption of IoT technology will make the management of fundamental operations such as ship monitoring, greenhouse gas emissions control, maintenance planning and safety more effective (Plaza-Hernández et al., 2021). The adoption of new digital technologies and automated systems raises the standard of strategic planning and communication strategies, workforce working conditions, and maritime supply chain stakeholders' productivity (Parola et al., 2021). Kozak-Holland and Procter (2020) point out that the Information Technology (IT) department of businesses has important duties to overcome the challenges of digital transformation. Tsiulin et al. (2023) have identified and summarized the challenges associated with the implementation of blockchain technology in the maritime industry and sea ports.

Cost is one of the major barriers to adoption of digital transformation technologies. The most important of these costs is the high cost of the initial investment. The payment of a significant amount of funds to a technology provider for work on a 'private blockchain' is a risk that could hamper its implementation in the maritime industry (Zhou et al., 2020). The willingness of the user to switch to the new system is significantly and negatively influenced by varying conversion costs due to economic risks, evaluation costs, learning costs and consumer acceptance (Ho and Hsu, 2020). The conservative culture of decision makers in maritime companies is another barrier to the adoption of digital transformation (Gausdal et al., 2018, Zhou et al., 2020). In addition to the adaptation of digital technologies, the implementation of secure systems that ensure the protection of the organisational infrastructure and operating systems against cyber attacks is imperative (Fruth and Teuteberg, 2017; Tijan et al., 2021). The implementation of DT requires the utilisation of distinct skill sets and the involvement of individuals within the organisational structure who possess a different set of competencies compared to those who are more experienced and adhere to more traditional (Raza et al., 2023). The potential for significant organisational change raises concerns among senior managers about their organisations' capacity to embrace such a transformative shift. These leaders perceive a lack of requisite knowledge, tools and commitment within their organisations to navigate the complexities of such a profound change (Mugge et al., 2020). Another managerial obstacle is the resistance of managers and employees due to not having the necessary skills (Durão et al., 2019). The country-specific nature of regulations in the field of maritime transport also gives rise to difficulties in the implementation of new Technologies (Tijan et al., 2021). Stakeholders at the maritime sector (e.g., shippers, consignees, shipping agents) face obstacles to digital transformation operations that other businesses experience, such as lack of awareness, absence of effective strategies and initiatives, and lack of resources for successful digital transformation (Tan and Sundarakani, 2021; Tijan et al., 2021, Raza et al., 2023). Table 1 presents the identified barriers, their classifications, and the authors who employed these barriers in their respective studies.

Table 1. Identified barriers to adopting DT in the maritime sector

Barrier type	*Barriers*	*References*
Technology (B1)		
B11	Cost	Ho and Hsu (2020), Zhou et al. (2020)
B12	Conservatism	Gausdal et al. (2018), Zhou et al. (2020)
B13	Decreased cyber security levels	Fruth and Teuteberg (2017), Tijan et al. (2021)
Organisation (B2)		
B21	Lack of sufficient human resources	Raza et al. (2023)
B22	Lack of knowledge	Mugge et al. (2020)
B23	Employees' and managers' resistance to change	Durão et al. (2019)
B24	Inadequate or absent regulations	Tijan et al. (2021)
Environment (B3)		
B31	Lack of coordination and cooperation in the partner ecosystem	Raza et al. (2023), Tan and Sundarakani (2021), Tijan et al. (2021)
B32	Laws and regulations	Zhou et al. (2020)
B33	Government/policy-makers support	Tijan et al. (2021)
Security (B4)		
B41	Information system insecurity	Nguyen et al. (2019), Sarker et al. (2021)
B42	Data protection and security breach	Cichosz et al. (2020)
B43	Lack of information security management	Gebremeskel et al. (2023)

This study sought to address this gap in the literature by employing a multi-criteria decision-making (MCDM) technique based on the spherical fuzzy-AHP (SF-AHP) (Kutlu Gündoğdu and Kahraman, 2020b) method to rank the barriers to digital transformation in maritime logistics. A total of thirteen barriers were identified and grouped into four main categories. The SF-AHP was then utilized to determine the relative weights and ranks of each barrier. Table 2 summarizes the prominent studies in the literature.

Table 2. Literature review summary

Author(s)	*Aim of the study*	*Methods used*
Heilig et al. (2017)	To identify current potentials and barriers, an overview of the development and status of digital transformation in modern seaports	Game theory
Tijan et al. (2021)	A summarized model of the drivers, factors, and barriers for digital transformation in maritime transport	Literature review
Bocayuva (2021)	Port cybersecurity aanalyzed in view of digital transformation	-
Jović et al. (2022)	A model of the factors that influence the digital transformation in the maritime transport sector	Literature review and Questionnaire survey
Parhi et al. (2022)	A total of fifteen enabling factors for the implementation of sustainable logistics 4.0 are identified and subjected to critical evaluation, with particular emphasis on firms at disparate levels of digitalization	F-AHP, DEMATEL
Tsiulin et al. (2023)	To identify and summarize the challenges of blockchain implementation in the maritime industry and sea ports	Literature review and previous research findings
Raza et al. (2023)	To examine in liner shipping companies, the current digital maturity levels, the opportunities afforded by digitalisation and the underlying challenges that impede its implementation in the liner shipping segment within the broader maritime logistics industry. It also identifies the essential leading strategies of digitalisation in this segment	Semi-structured interviews
Hamidi et al. (2024)	A three-stage digital maturity model that is designed to effectively gauge digital preparedness within the context of maritime logistics industries	F-AHP, F-TOPSIS
Utama et al. (2024)	To develop the digital transformation maturity model for ports	Literature review and Focus Group Discussion

3. METHODOLOGY

3.1. Spherical Fuzzy Sets: Preliminaries

The theory of fuzzy sets was first proposed by Zadeh (1965) as a way to deal with the doubt and ambiguity that frequently accompanies decision-making processes. The spherical fuzzy set (SFS) approach, which builds upon the foundations of Neutrosophic set (NS) and Pythagorean fuzzy set (PyFS), was firstly introduced by Kutlu Gündoğdu and Kahraman (2019a). This novel approach offers a robust framework for navigating the inherent ambiguity of data. SFS represents a novel expansion of the fuzzy set concept, offering a means of expressing the degree of membership, non-membership, and hesitancy as perceived by experts (Liu et al., 2023). Figure 1 depicts the historical development of fuzzy sets.

Figure 1. The history of the development of fuzzy sets

Spherical Fuzzy Sets (SFSs) afford decision-makers a more expansive domain of preference, and each of them is also able to ascertain their degree of hesitancy within the context of a spherical fuzzy environment (Donyatalab et al., 2022). In spherical fuzzy sets, the sum of the squares of the three parameters (membership, non-membership and hesitancy) can be in the interval [0, 1], while each can be defined independently in the interval [0, 1] (Kutlu Gündoğdu and Kahraman (2019b). This section presents the preliminary concepts of SFSs (Kutlu Gündoğdu and Kahraman, 2019b; Donyatalab et al., 2022).

Definition 1: The definition of an SFs, $\tilde{T}_s$, of the universe of discourse U is as follows (Equation 1):

$$\tilde{T}_s = \left\{\langle u, \left(\beta_{\tilde{T}_s}(u), \gamma_{\tilde{T}_s}(u), \delta_{\tilde{T}_s}(u)\right)\rangle \,|u \in U\right\} \tag{1}$$

Where $\beta_{\tilde{T}_s}: U \to [0,1]$, $\gamma_{\tilde{T}_s}: U \to [0,1]$, $\delta_{\tilde{T}_s}: U \to [0,1]$, and

For each, $\beta_{\tilde{T}_s}(u), \gamma_{\tilde{T}_s}(u), and\ \delta_{\tilde{T}_s}(u)$ are the degree of membership, non-membership, and hesitancy of u to $\tilde{T}_s$, respectively (Equation 2).

$$0 \le \beta^2_{\tilde{T}_s}(u) + \gamma^2_{\tilde{T}_s}(u) + \delta^2_{\tilde{T}_s}(u) \le 1 \quad (u \in U) \tag{2}$$

Definition 2: The following section presents the computations for the basic operators defined in the context of SFS. The operators are defined as follows Equations 3-6.

Addition:

$$\tilde{T}_s \oplus \tilde{P}_s = \left\{\sqrt{\beta^2_{\tilde{T}_s} + \beta^2_{\tilde{P}_s} - \beta^2_{\tilde{T}_s}.\beta^2_{\tilde{P}_s}}, \gamma^2_{\tilde{T}_s}.\gamma^2_{\tilde{P}_s}, \sqrt{\left(\left(1-\beta^2_{\tilde{P}_s}\right)\delta^2_{\tilde{T}_s} + \left(1-\beta^2_{\tilde{T}_s}\right)\delta^2_{\tilde{P}_s} - \delta^2_{\tilde{T}_s}.\delta^2_{\tilde{P}_s}\right)}\right\} \tag{3}$$

Multiplication:

$$\tilde{T}_s \otimes \tilde{P}_s = \left\{\beta^2_{\tilde{T}_s}.\beta^2_{\tilde{P}_s}, \sqrt{\gamma^2_{\tilde{T}_s} + \gamma^2_{\tilde{P}_s} - \gamma^2_{\tilde{T}_s}.\gamma^2_{\tilde{P}_s}}, \sqrt{\left(\left(1-\gamma^2_{\tilde{P}_s}\right)\delta^2_{\tilde{T}_s} + \left(1-\gamma^2_{\tilde{T}_s}\right)\delta^2_{\tilde{P}_s} - \delta^2_{\tilde{T}_s}.\delta^2_{\tilde{P}_s}\right)}\right\} \tag{4}$$

Multiplication by a scalar:

$$\tilde{T}_s \otimes x = \left\{ \sqrt{1-\left(1-\beta_{\tilde{T}_s}^2\right)^x}, \gamma_{\tilde{T}_s}^x, \sqrt{\left(1-\beta_{\tilde{T}_s}^2\right)^x - \left(1-\beta_{\tilde{T}_s}^2 - \delta_{\tilde{T}_s}^2\right)^x} \right\} \tag{5}$$

x. Power of $\tilde{T}_s$:

$$\tilde{T}_s^x = \left\{ \beta_{\tilde{T}_s}^x, \sqrt{1-\left(1-\gamma_{\tilde{T}_s}^2\right)^x}, \sqrt{\left(1-\gamma_{\tilde{T}_s}^2\right)^x - \left(1-\gamma_{\tilde{T}_s}^2 - \delta_{\tilde{T}_s}^2\right)^x} \right\} \tag{6}$$

Definition 3: The definition of Spherical Weighted Arithmetic Mean $(SWAM)_{\omega=}(\omega_1, \omega_1, \ldots, \omega_n); \sum_{i=1}^{n} \omega_i = 1$ is as follows (Equation 7):

$$\text{SWAM}_\omega \left(\tilde{T}_{s1}, \tilde{T}_{s2}, \ldots, \tilde{T}_{sn}\right) = \omega_1 \tilde{T}_{s1} + \omega_2 \tilde{T}_{s2} + \ldots + \omega_n \tilde{T}_{sn}$$

$$= \left\{ \sqrt{1-\prod_{i:1}^{n}\left(1-\beta_{\widetilde{T_{si}}}^2\right)^{\omega_i}}, \prod_{i:1}^{n} \gamma_{\widetilde{T_{si}}}^{\omega_i}, \sqrt{\prod_{i:1}^{n}\left(1-\beta_{\widetilde{T_{si}}}^2\right)^{\omega_i} - \prod_{i:1}^{n}\left(1-\beta_{\widetilde{T_{si}}}^2 - \delta_{\widetilde{T_{si}}}^2\right)^{\omega_i}} \right\} \tag{7}$$

3.2. Spherical Fuzzy AHP (SF-AHP)

Step 1: The initial stage of the process involves the establishment of a hierarchical structure.

Step 2: A spherical fuzzy pairwise comparison matrix $\tilde{\boldsymbol{P}} = \left[\tilde{\boldsymbol{P}}_{\boldsymbol{ij}}\right]_{\boldsymbol{nxn}}$ is constructed using the information obtained from the decision makers. The linguistic terms defined in Table 3, are used to express the opinions of decision makers. $\tilde{P} = \left[\tilde{P}_{ij}\right]_{nxn}$ is calculated using Equation 8.

$$\tilde{P} = \left[\tilde{P}_{ij}\right]_{nxn} = \begin{bmatrix} 1 & \tilde{T}_{12} & \ldots & \tilde{T}_{1n} \\ \tilde{T}_{21} & 1 & \cdots & \tilde{T}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{T}_{n1} & \tilde{T}_{n2} & \ldots & 1 \end{bmatrix} \; where\ i = j = 1,2, \ldots, n\ and\ \tilde{T}_{ij} = \left(\beta_{\tilde{T}_{ij}}, \gamma_{\tilde{T}_{ij}}, \delta_{\tilde{T}_{ij}}\right). \tag{8}$$

Table 3. The scale of SF linguistic terms

Linguistic Terms	*Spherical Fuzzy Numbers (SFNs)* (β, γ, δ)	*Score Index (SI)*
Absolutely more importance (AMI)	(0.9, 0.1, 0.0)	9
Very high importance (VHI)	(0.8, 0.2, 0.1)	7
High importance (HI)	(0.7, 0.3, 0.2)	5
Slightly more importance (SMI)	(0.6, 0.4, 0.3)	3
Equal importance (EI)	(0.5, 0.4, 0.4)	1
Slightly low importance (SLI)	(0.4, 0.6, 0.3)	1/3
Low importance (LI)	(0.3, 0.7, 0.2)	1/5
Very low importance (VLI)	(0.2, 0.8, 0.1)	1/7
Absolutely low importance (ALI)	(0.1, 0.9, 0.0)	1/9

Source: Kutlu Gündoğdu and Kahraman (2020b)

The score indices (SI) in Table 3 are calculated using the Equations 9 and 10.

For AMI, VHI, HI, SMI, and EI

$$SI = \sqrt{\left|100 \times \left(\left(\beta_{\tilde{U}_s} - \delta_{\tilde{U}_s}\right)^2 - \left(\gamma_{\tilde{U}_s} - \delta_{\tilde{U}_s}\right)^2\right)\right|} \tag{9}$$

For EI; SLI; LI; VLI; and ALI;

$$SI^{-1} = 1 \Big/ \sqrt{\left|100 \times \left(\left(\beta_{\tilde{U}_s} - \delta_{\tilde{U}_s}\right)^2 - \left(\gamma_{\tilde{U}_s} - \delta_{\tilde{U}_s}\right)^2\right)\right|} \tag{10}$$

Step 3: The pairwise comparison matrix is checked for consistency. The defuzzified crisp numbers are subjected to a comparison with the SFNs presented in Table 3, with the use of Saaty's scale. Then Saaty's classical consistency formula is employed. The spherical fuzzy pairwise comparison matrix is deemed consistent if the consistency ratio (CR) is smaller than 0.1.

Step 4: Calculate the spherical fuzzy local weights for each criterion. The weighted arithmetic mean is utilized to compute the spherical fuzzy weights; the spherical weights of each criterion is determined using the SWAM operator given in Equation 7.

Step 5: Use the score function *(S)* in Equation 11 to defuzzify the criteria weights and then Equation 12 to normalize to determine the final weights (Kutlu Gündoğdu and Kahraman, 2020b).

$$S(\tilde{\omega}_j^s) = \sqrt{\left|100 \times \left[\left(3\beta_{\tilde{T}_s} - \frac{\delta_{\tilde{T}_s}}{2}\right)^2 - \left(\frac{\gamma_{\tilde{T}_s}}{2} - \delta_{\tilde{T}_s}\right)^2\right]\right|} \quad (11)$$

$$\bar{\omega}_j^s = \frac{S(\tilde{\omega}_j^s)}{\sum_{j=1}^{n} S(\tilde{\omega}_j^s)} \quad (12)$$

4. AN ILLUSTRATION OF AN APPLICATION

The proposed method is an application to identify and determine the relative importance of barriers in the digital transformation process of companies in maritime logistics; more details are provided in following. Following a comprehensive literature review, a decision team consisting of three decision makers (DM1, DM2, DM3) experienced in maritime logistics is formed during the data collection process. In this context, four barriers (Technology (B1), Organisation (B2), Environment (B3), and Security (B4)) and 13 sub-barriers were determined based on expert opinions and literature review. Figure 2 illustrates this hierarchy, which comprises all identified barriers and sub- barriers.

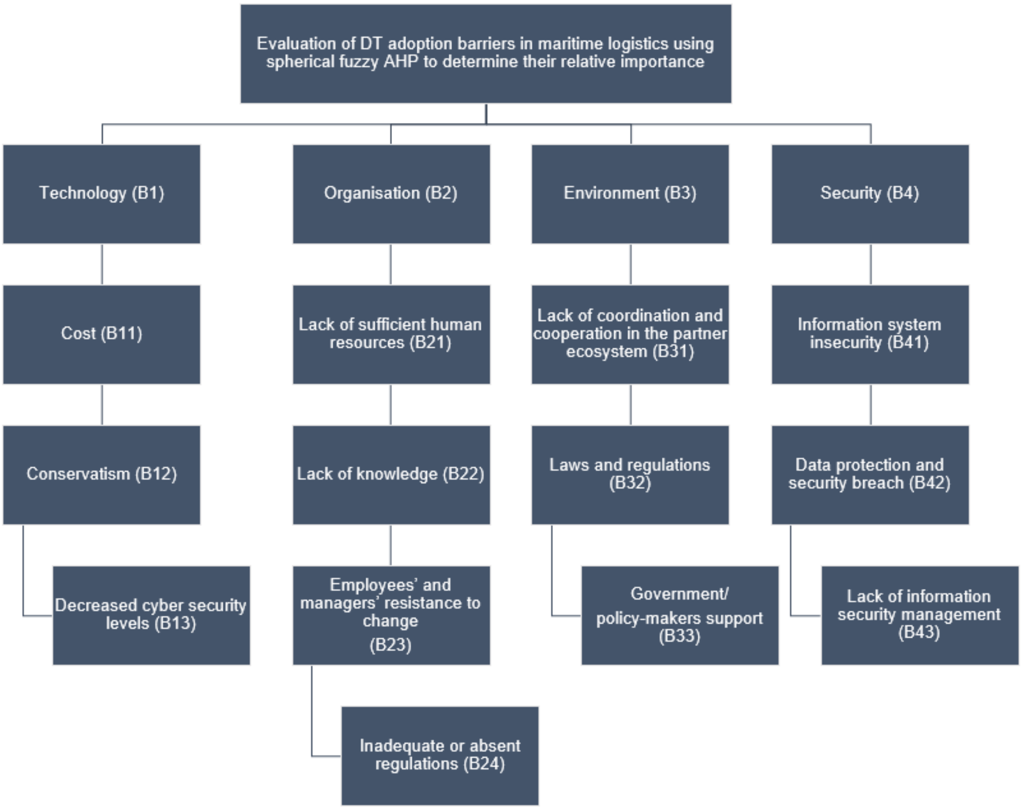

Figure 2. The developed decision hierarchy of barriers to adopting DT in maritime logistics

The CRs of the pairwise comparison matrices are computed in accordance with the corresponding numerical values in the classical AHP method for the linguistic scale delineated in Table 3. The pairwise comparisons and the computed spherical weights ($\tilde{\boldsymbol{\omega}}^s$) and crisp weights ($\bar{\boldsymbol{\omega}}^s$) are presented in Tables 4-13 including their CRs. In Table 14, the local and global weights of each sub-barrier are presented.

Table 4. Pairwise comparison of main barriers

Main Barriers		*B1*	*B2*	*B3*	*B4*
DM1	B1	EI	VHI	HI	SMI
CR= 0.044	B2	VLI	EI	SLI	LI
	B3	LI	SMI	EI	SLI
	B4	SLI	HI	SMI	EI
DM2		B1	B2	B3	B4
CR= 0.085	B1	EI	HI	SMI	HI
	B2	LI	EI	SLI	LI
	B3	SLI	SMI	EI	EI
	B4	LI	HI	EI	EI
DM3		B1	B2	B3	B4
CR= 0.064	B1	EI	AMI	VHI	HI
	B2	ALI	EI	SLI	LI
	B3	VLI	SMI	EI	SLI
	B4	LI	HI	SMI	EI

Table 5. Spherical weights of the main barriers

Main Barriers		$\widetilde{\boldsymbol{\omega}}^s$		$\overline{\boldsymbol{\omega}}^s$
B1	0.69	0.31	0.25	0.341
B2	0.37	0.61	0.29	0.171
B3	0.48	0.50	0.32	0.223
B4	0.55	0.42	0.30	0.266

Table 6. Pairwise comparison of "Technology related" barriers

Technology		*B11*	*B12*	*B13*
DM1	B11	EI	LI	SMI
CR=0.057	B12	HI	EI	VHI
	B13	SLI	VLI	EI
DM2		B11	B12	B13
CR=0.033	B11	EI	SLI	SMI
	B12	SMI	EI	HI
	B13	SLI	LI	EI
DM3		B11	B12	B13
CR=0.006	B11	EI	SLI	SMI
	B12	SMI	EI	VHI
	B13	SLI	VLI	EI

Table 7. Spherical weights of the "Technology related" barriers

Technology		$\widetilde{\omega}^s$		$\overline{\omega}^s$
B11	0.50	0.47	0.33	0.319
B12	0.65	0.33	0.27	0.434
B13	0.40	0.57	0.31	0.247

Table 8. Pairwise comparison of "Organisation related" barriers

Organisation		*B21*	*B22*	*B23*	*B24*
DM1	B21	EI	HI	LI	SMI
CR=0.091	B22	LI	EI	VLI	SLI
	B23	HI	VHI	EI	HI
	B24	SLI	SMI	LI	EI
DM2		B21	B22	B23	B24
CR=0.052	B21	EI	VHI	SLI	SMI
	B22	VLI	EI	VLI	SLI
	B23	SMI	VHI	EI	HI
	B24	SLI	SMI	LI	EI
DM3		B21	B22	B23	B24
CR=0.060	B21	EI	VHI	SLI	SMI
	B22	VLI	EI	VLI	SLI
	B23	SMI	VHI	EI	SMI
	B24	SLI	SMI	SLI	EI

Table 9. Spherical weights of the "Organisation related" barriers

Organisation		$\tilde{\omega}^s$		$\bar{\omega}^s$
B21	0.60	0.40	0.28	0.287
B22	0.36	0.62	0.28	0.164
B23	0.67	0.32	0.26	0.329
B24	0.48	0.50	0.32	0.220

Table 10. Pairwise comparison of "Environment related" barriers

Environment		*B31*	*B32*	*B33*
DM1	B31	EI	LI	VLI
CR=0.056	B32	HI	EI	SLI
	B33	VHI	SMI	EI
		B31	B32	B33
DM2	B31	EI	LI	ALI
CR=0.025	B32	HI	EI	SLI
	B33	AMI	SMI	EI
		B31	B32	B33
DM3	B31	EI	VLI	ALI
CR=0.070	B32	VHI	EI	SLI
	B33	AMI	SMI	EI

Table 11. Spherical weights of the "Environment related" barriers

Environment		$\tilde{\omega}^s$		$\bar{\omega}^s$
B31	0.34	0.64	0.28	0.198
B32	0.58	0.40	0.29	0.354
B33	0.71	0.28	0.25	0.447

Table 12. Pairwise comparison of "Security related" barriers

Security		*B41*	*B42*	*B43*
DM1	B41	EI	VHI	HI
CR=0.057	B42	VLI	EI	SLI
	B43	LI	SMI	EI
		B41	B42	B43
DM2	B41	EI	AMI	HI
CR=0.025	B42	ALI	EI	SLI
	B43	LI	SMI	EI
		B41	B42	B43
DM3	B41	EI	AMI	SMI
CR=0.000	B42	ALI	EI	SLI
	B43	SLI	SMI	EI

Table 13. Spherical weights of the "Security related" barriers

Security		$\tilde{\omega}^s$		$\bar{\omega}^s$
B41	0.73	0.27	0.23	0.470
B42	0.38	0.59	0.31	0.227
B43	0.50	0.48	0.33	0.302

"Technology" is the most important barrier category (B1) (0.341) for the adoption of digital transformation in maritime logistics, followed by the main barrier categories related to "Security" (B4) (0.266), "Environment" (B3) (0.223) and "Organisation" (B2) (0.171) respectively. Subsequently, the relative importance weights of the specific barriers were calculated. Additionally, global preference weights of the specific barriers were calculated, and their corresponding relative importance order or ranks were determined. Further details are provided in Table 14. Furthermore, the ranking results of the global weights of the calculated barriers are presented in Figure 3.

Table 14. Local and global weights of each sub-barrier

Barrier Type	*Main Barrier Weight*	*Local Weights*	*Global Weights*	*Rank*
B1	0.341			
B11		0.319	0.109	3
B12		0.434	0.148	1
B13		0.247	0.084	5
B2	0.171			
B21		0.287	0.049	10
B22		0.164	0.028	13
B23		0.329	0.056	9
B24		0.220	0.038	12
B3	0.223			
B31		0.198	0.044	11
B32		0.354	0.079	7
B33		0.447	0.100	4
B4	0.266			
B41		0.470	0.125	2
B42		0.227	0.060	8
B43		0.302	0.080	6

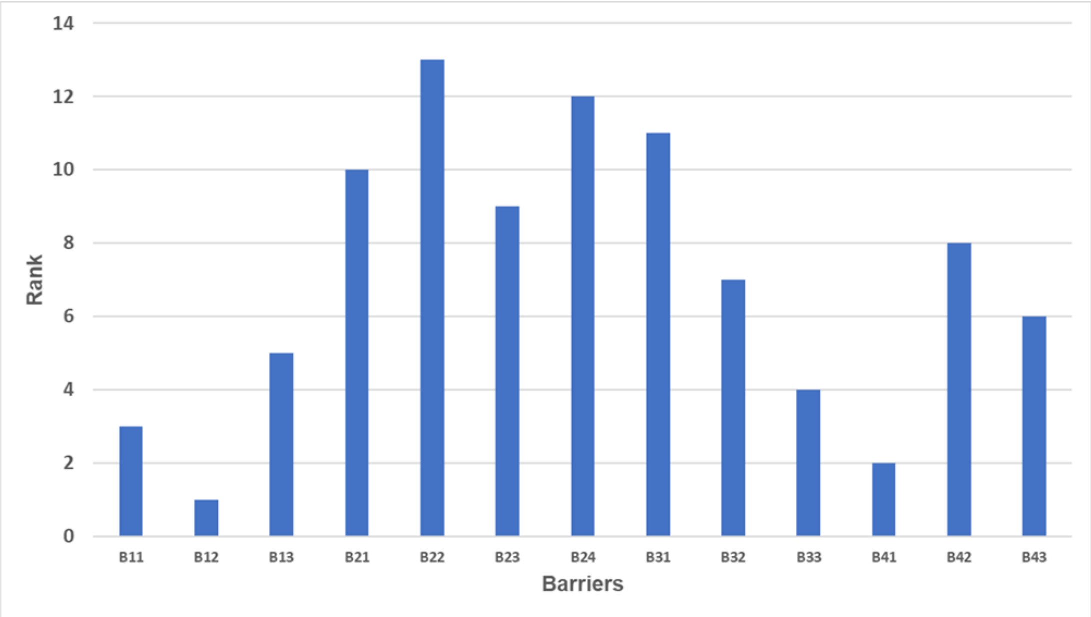

Figure 3. Ranking results of sub-barriers

4.1. Comparative Analysis

In order to ascertain the validity of the proposed method, it was subjected to comparison with the traditional AHP (Method 1) and Fermatean fuzzy AHP (Method 2) (Ayvaz et al., 2024) methods. As illustrated in Table 15, Table 16, Table 17, Table 18 and Table 19, the relative importance assigned to the barriers remains consistent in both the traditional AHP (AHP) and the Fermatean fuzzy AHP (FF-AHP) approaches. Furthermore, Figure 4 presents a comparative analysis of the relative importance weights of the barriers for the proposed method, the traditional AHP, and the FF-AHP, as illustrated graphically.

Table 15. Comparison of weights of the main barriers in SF-AHP, AHP and FF-AHP

	Proposed method	*Method 1*	*Method 2*
Main Barriers	*SF-AHP*	*AHP*	*FF-AHP*
B1	0.341	0.588	0.698
B2	0.171	0.058	0.029
B3	0.223	0.132	0.091
B4	0.266	0.223	0.182

Table 16. Comparison of weights of the Technology sub-barriers in SF-AHP, AHP and FF-AHP

Technology Sub-Barriers	*Proposed method*	*Method 1*	*Method 2*
	SF-AHP	*AHP*	*FF-AHP*
B11	0.319	0.231	0.228
B12	0.434	0.677	0.682
B13	0.247	0.092	0.091

Table 17. Comparison of weights of the Organisation sub-barriers in SF-AHP, AHP and FF-AHP

Organisation Sub-Barriers	*Proposed method*	*Method 1*	*Method 2*
	SF-AHP	*AHP*	*FF-AHP*
B21	0.287	0.270	0.239
B22	0.164	0.054	0.027
B23	0.329	0.551	0.650
B24	0.220	0.125	0.084

Table 18. Comparison of weights of the Environment sub-barriers in SF-AHP, AHP and FF-AHP

Environment Sub-Barriers	*Proposed method*	*Method 1*	*Method 2*
	SF-AHP	*AHP*	*FF-AHP*
B31	0.198	0.064	0.063
B32	0.354	0.282	0.278
B33	0.447	0.654	0.659

Table 19. Comparison of weight of the Security sub-barriers in SF-AHP, AHP and FF-AHP

Security Sub-Barriers	*Proposed method*	*Method 1*	*Method 2*
	SF-AHP	*AHP*	*FF-AHP*
B41	0.470	0.723	0.726
B42	0.227	0.077	0.076
B43	0.302	0.200	0.198

4.2. Managerial Implications

The proposed methodology presents the experts' opinions regarding the main criteria and sub-criteria. The results indicate that technology and security are the two most significant main dimensions of DT. These findings are consistent with those reported in the existing literatüre (Parhi et al., 2022; Hamidi et al., 2024).

The advent of digital transformation has resulted in significant alterations to the structural business models of numerous industries, thereby enhancing the efficiency of business processes. However, it is important to recognise that each sector is confronted with a unique set of challenges and barriers during the digital transformation process. The technology dimension identified by experts as the most significant barrier to the adoption of digital transformation. The author provided a literature review in which four main dimensions (Technology, Organisation, Environment and Security) are considered as the most important factors for the digitalization of an industry. In accordance with expert assessments, the three most significant barriers to digital transformation in maritime logistics are conservatism, information system insecurity, and cost. In contrast to numerous other sectors, the maritime sector is frequently characterised by a familial structure and a networked approach to its stakeholders. This structural form has historically demonstrated a tendency towards conservatism with regard to the incorporation of innovative practices (Raza et al., 2023). The process of digital transformation is one that is gradual and time-consuming, necessitating substantial and effective investments (Utama et al., 2024). Another outcome of this study is the conclusion that information security is a crucial aspect of the digital transformation process. The logistics sector plays a significant role in global trade, engaging with a diverse range of stakeholders. In particular, maritime transportation represents the most highly percentage of all transportation modes. The maritime logistics sector, which handles high-value monetary transfers and large-volume cargo, can be targeted by cyber attacks (Bocayuva, 2021). The high cost and lengthy timeframe associated with digital transformation within the maritime logistics sector place significant responsibility on those in managerial roles. It is therefore incumbent upon maritime logistics companies to adopt a strategic approach to the digital transformation process, ensuring that their capabilities in this regard are clearly defined, that their infrastructure investments are completed, and that they lead the way in corporate innovation.

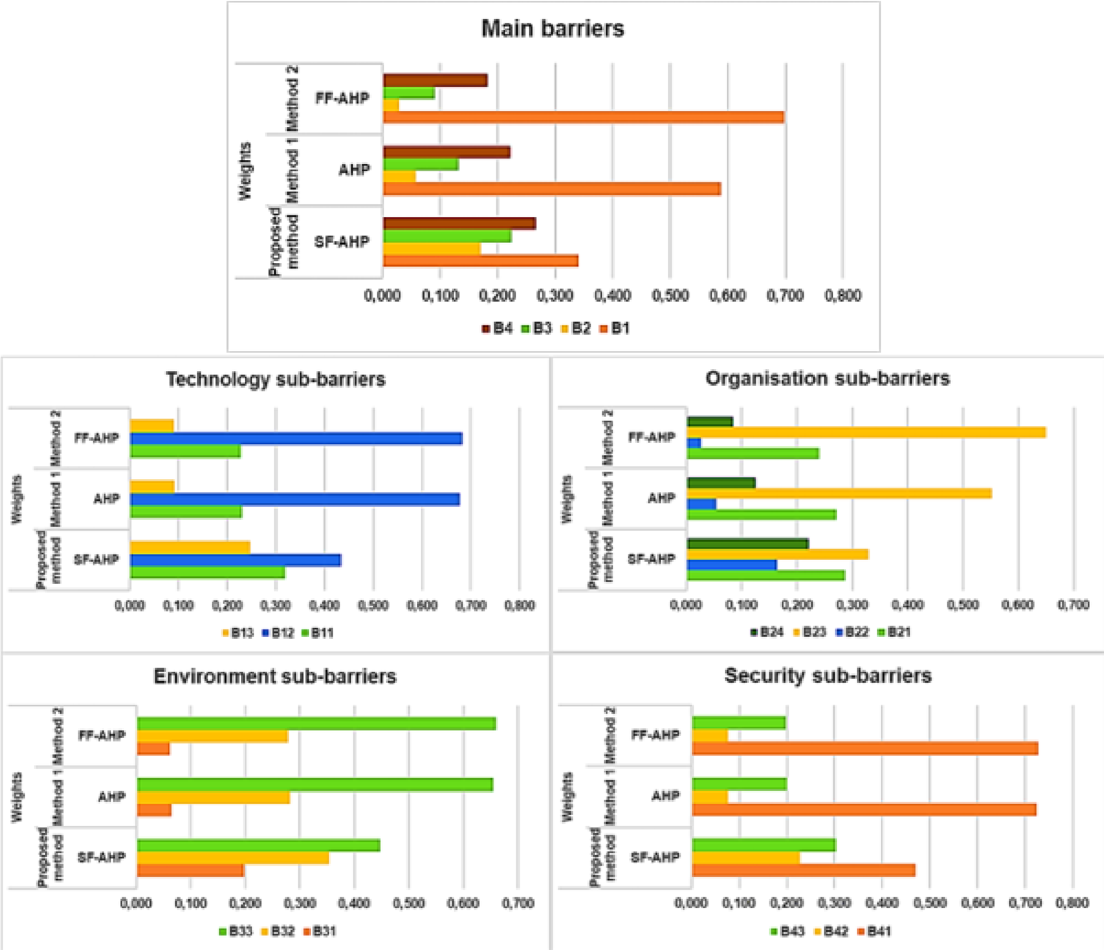

Figure 4. A graphical representation of the comparative analysis results

5. CONCLUSIONS

In the maritime logistics sector, transport operators and port stakeholders are at different phases of the digital transformation (DT) process (Tijan et al., 2021). While some ports, transport companies, etc. have achieved remarkable success in this regard, others have not reached sufficient effectiveness in fully implementing DT throughout the supply chain. Furthermore, the maritime industry is reluctant to assume the risk associated with the adoption of nascent technologies, and its traditionalist culture predisposes decision-makers towards a degree of conservatism (Zhou et al., 2020).

The motivation for this study is derived from the observation that the impediments to the maritime logistics sector's adoption of digital transformation have not been sufficiently evaluated and addressed through the application of diverse methodological approaches. In order to address this gaps, the present study seeks to identify and prioritize the potential barriers that may emerge during the digital transformation of maritime logistics operations. In order to achieve this objective, the author carried out an exhaustive review of the relevant literature.

This study contributes to the field in several ways, offering both theoretical and managerial implications for practitioners, policy makers and researchers involved in this area of research. Firstly, from theoretical point of view, this study identified and ranked four main barriers and 13 related sub-barriers to the adoption of DT in maritime logistics sector. The top five most concerned barriers are; “Conservatism” related to the Technology main barrier, “Information system insecurity” related to the Security main barrier, “Cost” related to the Technology main barrier, “Government/policy-makers support” related to the Environment barrier, and finally “Decreased cyber security levels” related to the Technology main barrier. The proposed approach employs the extended AHP methodology with spherical fuzzy sets (SFS), thus allowing decision makers more flexibility in assigning different values to the degrees of uncertainty in their judgements (degrees of membership, non-membership, and hesitancy degrees).

The main contributions of this study are as follows. First, a hierarchical structure model of the barriers to the adoption of DT in the maritime logistics sector. Secondly, a set of valid barriers to the implementation of digitalization in maritime logistics is proposed from the perspective of key stakeholders. Thirdly, this is the first study to utilize the AHP method based on SFS to evaluate the barriers in the digital transformation process in the maritime logistics sector. Fourth, to aggregate the judgment data of individual experts, a SWAM operator-based method is used to form an aggregate evaluation matrix. Fifth, the proposed approach will serve as a reference for experts and practitioners in the maritime logistics sector and provide crucial insights for the application of DT technologies. And comparative analysis is applied to verify the robustness and applicability of the proposed methodology.

The results of our study indicate that the digital transformation of the maritime logistics sector will be most effective when all stakeholders are encouraged to collaborate. This approach will lead to more efficient and effective operational processes within the sector. For future researches, the proposed method can be compared with different fuzzy set extensions (Pythagorean fuzzy set, picture fuzzy set) and different multi-criteria decision making methods.

Conflict of Interest
No potential conflict of interest was declared by the author.

Funding
Any specific grant has not been received from funding agencies in the public, commercial, or not-for-profit sectors.

Compliance with Ethical Standards
It was declared by the author that the tools and methods used in the study do not require the permission of the Ethics Committee.

Ethical Statement
It was declared by the author that scientific and ethical principles have been followed in this study and all the sources used have been properly cited.

REFERENCES

Ahmad, R. W., Hasan, H., Jayaraman, R., Salah, K. and Omar, M. (2021). "Blockchain Applications and Architectures for Port Operations and Logistics Management", *Research in Transportation Business & Management*, 41, 100620.

Ayvaz, B., Tatar, V., Sağır, Z. and Pamucar, D. (2024). "An Integrated Fine-Kinney Risk Assessment Model Utilizing Fermatean Fuzzy AHP-WASPAS for Occupational Hazards in the Aquaculture Sector", *Process Safety and Environmental Protection*, 186, 232-251.

Babica, V., Sceulovs, D. and Rustenova, E. (2020). "Digitalization in Maritime Industry: Prospects and Pitfalls", *ICTE in Transportation and Logistics 2019,* Springer International Publishing, 20-27.

Bocayuva, M. (2021). "Cybersecurity in the European Union Port Sector in Light of the Digital Transformation and the COVID-19 Pandemic", *WMU Journal of Maritime Affairs*, 20, 173-192.

Cichosz, M., Wallenburg, C.M. and Knemeyer, A.M. (2020). "Digital Transformation at Logistics Service Providers: Barriers, Success Factors and Leading Practices", *The International Journal of Logistics Management*, 31(2), 209-238.

Del Giudice, M., Di Vaio, A., Hassan, R. and Palladino, R. (2022). "Digitalization and New Technologies for Sustainable Business Models at the Ship–Port Interface: A Bibliometric Analysis", *Maritime Policy & Management*, 49(3), 410-446.

Dogan, O. (2021). "Process Mining Technology Selection with Spherical Fuzzy AHP and Sensitivity Analysis", *Expert Systems with Applications*, 178, 114999.

Donyatalab, Y., Gündoğdu, F.K., Farid, F., Seyfi-Shishavan, S.A., Farrokhizadeh, E. and Kahraman, C. (2022). "Novel Spherical Fuzzy Distance and Similarity Measures and Their Applications to Medical Diagnosis", *Expert Systems with Applications*, 191, 116330.

Durão, N., Ferreira, M.J., Pereira, C.S. and Moreira, F. (2019). "Current and Future State of Portuguese Organizations towards Digital Transformation", *Procedia Computer Science*, 164, 25-32.

Fruth, M. and Teuteberg, F. (2017). "Digitization in Maritime Logistics—What Is There and What Is Missing?", *Cogent Business & Management*, 4(1), 1411066.

Gausdal, A.H., Czachorowski, K.V. and Solesvik, M.Z. (2018). "Applying Blockchain Technology: Evidence from Norwegian Companies" *Sustainability*, 10(6), 1985.

Gebremeskel, B.K., Jonathan, G.M. and Yalew, S.D. (2023). "Information Security Challenges during Digital Transformation", *Procedia Computer Science*, 219, 44-51.

Hamidi, S.M.M., Hoseini, S.F., Gholami, H. and Kananizadeh-Bahmani, M. (2024). "A Three-Stage Digital Maturity Model to Assess Readiness Blockchain Implementation in Maritime Logistics Industry", *Journal of Industrial Information Integration*, 100643.

Heilig, L., Lalla-Ruiz, E. and Voß, S. (2017). "Digital Transformation in Maritime Ports: Analysis and A Game Theoretic Framework", *Netnomics: Economic Research and Electronic Networking*, 18(2), 227-254.

Ho, T.C. and Hsu, C.L. (2020). "An Analysis of Key Factors Influencing Integration of Blockchain into Shipping Companies in Taiwan", *Journal of Marine Science and Technology*, 28(4), 1.

Ichimura, Y., Dalaklis, D., Kitada, M. and Christodoulou, A. (2022). "Shipping in the Era of Digitalization: Mapping the Future Strategic Plans of Major Maritime Commercial Actors", *Digital Business*, 2(1), 100022.

Jović, M., Tijan, E., Vidmar, D. and Pucihar, A. (2022). "Factors of Digital Transformation in the Maritime Transport Sector", *Sustainability*, 14(15), 9776.

Kache, F. and Seuring, S. (2017). "Challenges and Opportunities of Digital Information at the Intersection of Big Data Analytics and Supply Chain Management", *International Journal of Operations & Production Management*, 37(1), 10-36.

Kahraman, C. and Kutlu Gündoğdu, F. (2018). "From 1D to 3D Membership: Spherical Fuzzy Sets", BOS / SOR 2018 Conference, Warsaw, Poland.

Kechagias, E.P., Chatzistelios, G., Papadopoulos, G.A. and Apostolou, P. (2022). "Digital Transformation of the Maritime Industry: A Cybersecurity Systemic Approach", *International Journal of Critical Infrastructure Protection*, 37, 100526.

Kozak-Holland, M. and Procter, C. (2020). "The Challenge of Digital Transformation", *Managing Transformation Projects*, Palgrave Pivot, Cham, 1-11.

Kumar, A. and Pant, S. (2023). "Analytical Hierarchy Process for Sustainable Agriculture: An Overview", *MethodsX*, 10, 101954.

Kutlu Gündoğdu, F. and Kahraman, C. (2019a). "Spherical Fuzzy Sets and Spherical Fuzzy TOPSIS Method", *Journal of Intelligent & Fuzzy Systems*, 36(1), 337-352.

Kutlu Gündoğdu, F. and Kahraman, C. (2019b). "A Novel Fuzzy TOPSIS Method Using Emerging Interval-Valued Spherical Fuzzy Sets", *Engineering Applications of Artificial Intelligence*, 85, 307-323.

Kutlu Gündoğdu, F. and Kahraman, C. (2020a). "A Novel Spherical Fuzzy QFD Method and Its Application to the Linear Delta Robot Technology Development", *Engineering Applications of Artificial Intelligence*, 87, 103348.

Kutlu Gündoğdu, F. and Kahraman, C. (2020b). "A Novel Spherical Fuzzy Analytic Hierarchy Process and Its Renewable Energy Application", *Soft Computing*, 24, 4607-4621.

Liu, Q., Chen, J., Yang, K., Liu, D., He, L., Qin, Q. and Wang, Y. (2023). "An Integrating Spherical Fuzzy AHP and Axiomatic Design Approach and Its Application in Human–Machine Interface Design Evaluation", *Engineering Applications of Artificial Intelligence*, 125, 106746.

Mugge, P., Abbu, H., Michaelis, T.L., Kwiatkowski, A. and Gudergan, G. (2020). "Patterns of Digitization: A Practical Guide to Digital Transformation", *Research-Technology Management*, 63(2), 27-35.

Nguyen, S., Chen, P.S.L., Du, Y. and Shi, W. (2019). "A Quantitative Risk Analysis Model with Integrated Deliberative Delphi Platform for Container Shipping Operational Risks", *Transportation Research Part E: Logistics and Transportation Review*, 129, 203-227.

Özkan, B., Erdem, M. and Özceylan, E. (2022). "Evaluation of Asian Countries Using Data Center Security Index: A Spherical Fuzzy AHP-Based EDAS Approach", *Computers & Security*, 122, 102900.

Panayides, P.M. and Song, D.W. (2013). "Maritime Logistics as An Emerging Discipline", *Maritime Policy & Management*, 40(3), 295-308.

Parhi, S., Joshi, K., Gunasekaran, A. and Sethuraman, K. (2022). "Reflecting on An Empirical Study of the Digitalization Initiatives for Sustainability on Logistics: The Concept of Sustainable Logistics 4.0", *Cleaner Logistics and Supply Chain*, 4, 100058.

Parola, F., Satta, G., Buratti, N. and Vitellaro, F. (2021). "Digital Technologies and Business Opportunities for Logistics Centres in Maritime Supply Chains", *Maritime Policy & Management*, 48(4), 461-477.

Plaza-Hernández, M., Gil-González, A.B., Rodríguez-González, S., Prieto-Tejedor, J. and Corchado-Rodríguez, J.M. (2021). "Integration of IoT Technologies in the Maritime Industry", *Distributed Computing and Artificial Intelligence, Special Sessions, 17th International Conference* (DCAI 2020), *Advances in Intelligent Systems and Computing*, 1242. Springer, Cham.

Raza, Z., Woxenius, J., Vural, C.A. and Lind, M. (2023). "Digital Transformation of Maritime Logistics: Exploring Trends İn The Liner Shipping Segment", *Computers in Industry*, *145*, 103811.

Saaty, T. L. (1977). "A Scaling Method for Priorities in Hierarchical Structures", *Journal of Mathematical Psychology*, 15(3), 234-281.

Sarker, S., Henningsson, S., Jensen, T. and Hedman, J. (2021). "The Use of bloCkchain as A Resource for Combating Corruption in Global Shipping: An Interpretive Case Study", *Journal of Management Information Systems*, 38(2), 338-373.

Statista. (2024). "Size of the Global Logistics Industry from 2018 to 2023, with Forecasts until 2028", https://www.statista.com/statistics/943517/logistics-industry-global-cagr/ (Accessed: 12.05.2024).

Tan, W.K.A. and Sundarakani, B. (2021). "Assessing Blockchain Technology Application for freight booking business: A case Study from Technology Acceptance Model Perspective", *Journal of Global Operations and Strategic Sourcing*, 14(1), 202-223.

Tijan, E., Jović, M., Aksentijević, S. and Pucihar, A. (2021). "Digital Transformation in the Maritime Transport Sector", *Technological Forecasting and Social Change*, 170, 120879.

Tsiulin, S., Reinau, K.H. and Hilmola, O. P. (2023). "The Key Challenges of Blockchain Implementation in Maritime Sector: Summary from Literature and Previous Research Findings", *Procedia Computer Science*, 217, 348-357.

UNCTAD (United Nations Conference on Trade and Development), (2020). "Transport and Trade Facilitation Series No. 13, Digitalizing the port call process", https://unctad.org/system/files/official-document/dtltlb2019d2_en.pdf (Accessed: 20.05.2024).

Utama, D.R., Hamsal, M., Abdinagoro, S.B. and Rahim, R.K. (2024). "Developing A Digital Transformation Maturity Model for Port Assessment in Archipelago Countries: The Indonesian Case", *Transportation Research Interdisciplinary Perspectives*, 26, 101146.

Vujičić, S., Hasanspahić, N., Car, M. and Čampara, L. (2020). "Distributed Ledger Technology as a Tool for Environmental Sustainability İn The Shipping İndustry", *Journal of Marine Science and Engineering*, 8(5), 366.

Wei, F., Alias, C. and Noche, B. (2019). "Applications of Digital Technologies in Sustainable Logistics and Supply Chain Management", Melkonyan, A., Krumme, K. (eds), *Innovative Logistics Services and Sustainable Lifestyles*. Springer, Cham, 235-263.

Yang, C.S. (2019). “Maritime Shipping Digitalization: Blockchain-Based Technology Applications, Future Improvements, and Intention to Use”, *Transportation Research Part E: Logistics and Transportation Review*, 131, 108-117.

Zadeh, L.A. (1965). “Fuzzy Sets”, *Information and Control*, 8(3), 338-353.

Zhou, Y., Soh, Y.S., Loh, H.S. and Yuen, K.F. (2020). “The Key Challenges and Critical Success Factors of Blockchain Implementation: Policy Implications for Singapore’s Maritime Industry”, *Marine Policy*, 122, 104265.

VERİMLİLİK DERGİSİ
JOURNAL OF PRODUCTIVITY

Assessment of Operational, Environmental and Social Performance of Container Ports in Türkiye

Esra Yıldırım Söylemez[1]

ABSTRACT

Purpose: This study aims to reveal the sustainability orientations of container port facilities operating in Turkey through sustainability reports and to evaluate the performance of their operational, environmental and social dimensions both separately and in an integrated manner (Environmental, Social, Operational-ESO).

Methodology: Sustainability orientations of container port facilities were subjected to qualitative assessment through examination of web pages and sustainability reports. The data obtained through document scanning regarding operational, environmental, and social performance indicators revealed by researching the relevant literature were analyzed using the MULTIMOORA method. The Rank Position Method was used in the performance ranking of port facilities.

Findings: The results show that 18% of the container service port facilities publish independent sustainability reports. There are deficiencies in the environmental and especially social performance indicators taken into account in the sustainability reports. Among the port facilities examined, Mersin International Port, which has the highest operational performance, is also ranked as the facility with the lowest integrated performance (ESO). The port facility with the highest integrated performance (ESO) was Socar.

Originality: The study contributes to filling the gap in the literature regarding the evaluation of environmental, social and operational performance of container ports in Turkey with the MULTIMOORA method. More importantly, the integrated examination of relevant performance dimensions represents the originality of this study.

Keywords: Container Ports, Sustainability Report, Environmental-Social-Operational Performance Indicators, MULTIMOORA.

JEL Codes: Q50, P47, C44.

Türkiye'deki Konteyner Limanlarının Operasyonel, Çevresel ve Sosyal Performansının Değerlendirilmesi

ÖZET

Amaç: Bu çalışmada sürdürülebilirlik raporları aracılığıyla Türkiye'de hizmet veren konteyner liman tesislerinin sürdürülebilirlik yönelimlerinin ortaya çıkarılması; operasyonel, çevresel ve sosyal boyutlarının hem ayrı ayrı hem de bütünleşik (Çevresel, Sosyal, Operasyonel-ESO) performanslarının değerlendirilmesi amaçlanmaktadır.

Yöntem: Konteyner liman tesislerinin sürdürülebilirlik yönelimleri, web sayfalarının ve sürdürülebilirlik raporlarının incelenmesi yoluyla nitel değerlendirmeye tabi tutulmuştur. İlgili literatürün taranmasıyla ortaya çıkarılan operasyonel, çevresel ve sosyal performans göstergelerine ilişkin belge tarama yoluyla elde edilen veriler MULTIMOORA yöntemi ile analiz edilmiştir. Liman tesislerinin performans sıralamasında Sıralı Pozisyon Yöntemi kullanılmıştır.

Bulgular: Sonuçlar, konteyner hizmeti veren liman tesislerinin %18'inin tesis özelinde bağımsız sürdürülebilirlik raporu yayınladığını göstermektedir. Sürdürülebilirlik raporlarında dikkate alınan çevresel ve özellikle sosyal performans göstergelerine ilişkin eksiklikler bulunmaktadır. İncelenen liman tesisleri arasında operasyonel performansı en yüksek olan Mersin Uluslararası Limanı aynı zamanda bütünleşik performansı (ESO) en düşük tesis olarak sıralanmıştır. Bütünleşik performansı (ESO) en yüksek liman tesisi Socar olmuştur.

Özgünlük: Çalışma, Türkiye'deki konteyner limanlarının çevresel, sosyal ve operasyonel performansının MULTIMOORA yöntemi ile değerlendirilmesine ilişkin literatürdeki boşluğun doldurulmasına katkıda bulunmaktadır. Daha önemlisi ilgili performans boyutlarının bütünleştirilerek incelenmesi bu çalışmanın özgünlüğünü temsil etmektedir.

Anahtar Kelimeler: Konteyner Limanları, Sürdürülebilirlik Raporu, Çevresel-Sosyal-Operasyonel Performans Göstergeleri, MULTIMOORA.

JEL Kodları: Q50, P47, C44.

[1] Kütahya Dumlupınar University, Faculty of Economics and Administrative Sciences, Department of Business Administration, Kütahya, Türkiye

Corresponding Author: Esra Yıldırım Söylemez, esra.yildirim@dpu.edu.tr

DOI: 10.51551/verimlilik.1529374
Research Article | Submitted: 07.08.2024 | Accepted: 04.11.2024
Cite: Yıldırım Söylemez, E. (2025). "Assessment of Operational, Environmental and Social Performance of Container Ports in Türkiye", *Verimlilik Dergisi,* Productivity for Logistics (SI), 45-62.

1. INTRODUCTION

The evolving consumer habits and the increasing diversification of customer demands have driven businesses to adopt strategies such as flexibility, global sourcing, and dispersed production facilities. This trend underscores the importance of maritime transport, which offers rapid and cost-effective logistics globally. According to the United Nations Conference on Trade and Development (UNCTAD, 2024), approximately 80% of international trade by volume is transported by sea. Over 60% of the global commercial value in maritime transport is handled through container ports (Humphreys, 2023). These ports have evolved into distribution centers within supply chains, acting as interfaces between production and consumption (Venus Lun et al., 2016; 50). Consequently, they are key players in international trade and global logistics, serving as critical nodes in maritime supply chains (Dong et al., 2019).

Container ports, as hubs of supply chains, significantly contribute to the socio-economic development of societies (Hossain et al., 2021). However, the expansion of resources associated with port activities has led to substantial negative environmental impacts, such as emissions and dredging waste (Lim et al., 2019). These negative impacts necessitate the adoption of a sustainability approach within the port sector. Majidi et al. (2021) argue that ports, as essential components of national economies and main channels for imports and exports, should be developed further, with more research focused on their environmental, social, and economic impacts. Sustainability in ports is defined as meeting current and future needs while conserving natural resources and the environment through proper resource utilization (Yorulmaz and Baykan, 2023). The primary objective of the sustainability approach in ports, based on the principle of sustainable development, is to adopt a safe, socially acceptable, energy-efficient, and environmentally friendly port management approach while maximizing profit (AAPA, 2007; 25).

While the sustainability approach examines the internal and external relationships provided by Environmental, Social and Governance (ESG) criteria from an organizational perspective, it requires businesses to manage environmental, social and economic risks and understand their short, medium and long-term effects in order to achieve competitive advantage (De Souza Barbosa et al., 2023). Environmental sustainability in ports aims to minimize the negative impacts of various operational and transport activities within and around the port (Lim et al., 2019). According to the European Sea Ports Organisation (ESPO) (2023; 6), the sector's top five environmental sustainability priorities are climate change, air quality, energy efficiency, noise, and water quality. These priorities encompass a wide range of issues, from emissions to biodiversity and waste management (Hossain et al., 2021). Social sustainability involves addressing socioeconomic priorities such as job creation, education for workers and the community, and improving quality of life to enhance social stability in the surrounding area (Lim et al., 2019). ESPO (2023; 19) emphasizes the dynamic interactions between ports and their regions, promoting positive port-city relationships and supporting collaborative approaches to sustainability, and social well-being. Economic sustainability in ports refers to maximizing economic performance through sustainable development initiatives without negatively impacting social and environmental development (Lim et al., 2019). Porter (2003; 2) states that businesses need to adapt to social and environmental demands alongside economic demands to gain a competitive advantage, which benefits both society and businesses. Sustainability literature suggests that businesses can enhance economic performance while reducing negative environmental impacts (Venus Lun et al., 2016; 79). Numerous findings support the view that improving environmental and social performance correlates positively with economic performance (Klassen and McLaughlin, 1996). Although there are practices aimed at reducing costs increasing productivity through energy efficiency and minimizing environmental impacts in ports, the relationship between environmental improvements and economic performance is not fully understood (Venus Lun et al., 2016; 4). Ashrafi et al. (2019) emphasize that despite the importance of the sustainability approach in most port facilities, it is not fully integrated into strategic decision-making and operations due to various challenges. One main challenge is determining sustainability performance indicators and actions needed to remain competitive and comply with the global sustainability agenda (Dong et al., 2019; Majidi et al., 2021).

Performance analysis is a fundamental indicator in all decisions, including investment decisions in container ports (Görçün, 2021). Evaluating sustainability performance in ports is complex due to the multidimensional nature of sustainability and its association with numerous internal and external factors, as well as the difficulty of incorporating environmentally friendly processes into decision-making and planning (Lim et al., 2019; Majidi et al., 2021). While research in operations management emphasizes that operational practices are closely related to the economic and environmental performance of businesses (Duong, 2022), it is stated that planning and managing operations are fundamental to achieving sustainability (Mangla et al., 2020). While being aware that the operational performance of ports is closely related to their economic performance (Nottebom et al., 2023) and considering that operational performance cannot fully meet the economic dimension of sustainability (since financial data is beyond the scope of this study), instead of the term sustainability performance, the term environmental, social and operational (ESO) performance was used for integrated performance in the study. Although it has been examined individually in different studies, the integrated examination of the relevant performance dimensions represents the originality of this study. The MULTIMOORA method used in this study will enrich the literature in terms of methodology in order to meet the need for practical and multidisciplinary techniques for the integrated analysis of different dimensions of sustainability (Lim et al., 2019; Stanković et al., 2021).

In Türkiye, container ports have significant potential to enhance existing container transportation due to their geographical location and port infrastructure (Utikad, 2023). This study is motivated by the inclusion of the sustainability approach among the priority issues for these ports. The study aims to determine the sustainability orientations of container port facilities in Türkiye and evaluate their environmental, social and operational performance. The subsequent sections of this study include a literature review, research design and method, findings, conclusions, and discussions.

2. LITERATURE REVIEW

Performance measurement enables organizations to assess how effectively and efficiently they achieve their goals through specific activities while guiding improvements (Woo et al., 2011). It is obtained through a set of indicators aligned with the strategic, tactical, and operational goals of the business (Bourne et al., 2003). Over the past thirty years, the increasing interest in performance measurement in ports within academia and industry has resulted in a growing number of studies (Lim et al., 2019). This section examines the literature on port performance evaluation in four parts: 1) operational performance indicators of ports, 2) environmental and social performance indicators, 3) research methodology, and 4) studies based on port performance measurement in Türkiye.

According to Bergantino et al. (2013), there is no consensus in academia and industry regarding the indicators that can be used to evaluate the performance of port facilities. The main reason for this is the complexity and diversity of operations carried out in ports. Traditionally, the operational performance of ports is determined by efficiency measures such as quay and gate productivity, maritime connectivity, and average berth access time (Karakas 2020). Ding and Chou (2011) have taken five main indicators as the basis for evaluating the service performance of container ports: container volume, port location, port charges, facilities, and service quality. With 31 sub-indicators (number of quay, quay water depth, quay length, number of equipment, storage capacity, efficiency, etc.) linked to these indicators, they have provided a comprehensive perspective on the evaluation of the operational performance of ports. Many studies have considered these performance indicators (Li et al., 2022; Kaya et al., 2023). The most commonly used performance metric, handled container (Sheikh et al. 2023; Kaya et al., 2023), has been expressed as annual throughput in some publications (Woo et al. 2011; Danladi et al., 2024; Li et al., 2022). Wang et al. (2021) argue that a port's handling capacity is a direct result of the port's level of development and is therefore an important dimension in measuring the port's economic success. They state that the capacity of port operations can be measured by the number of quay, overall efficiency, and the intensity of traffic with foreign ports. Iyer and Nanyam (2021a) and Nanyam and Jha (2022) also support the idea that the intensity of hinterland connections with other ports and the operational performance of new mainline services increase. Therefore, performance indicators such as accessibility, hinterland, and integration level with external markets have gained importance globally in terms of the supply chain (Karakas, 2020). Vrakas et al. (2021) and Wang et al. (2021) emphasize that technology use and standardization have become increasingly important performance indicators in recent years, parallel to technological advancements. However, it is still accepted that improving quay infrastructure, yard infrastructure, and overall infrastructure is important for improving operational performance (Nanyam and Jha, 2022).

Container transportation has gained importance in global trade due to its efficiency and fast service in cargo transportation (Akkan, 2022). However, this growth has worsened environmental problems such as air, and water pollution and resource depletion caused by ports and revealed the necessity of a sustainable approach. Modern port facilities must acquire new capabilities and adopt new practices (Lirn et al., 2013). Dong et al. (2019) note the growing interest in port sustainability. Venus Lun et al. (2016) and Roh et al. (2021) list essential practices for integrating sustainability into ports, including greenhouse gas emissions management, energy and water conservation, air quality, environmental quality, resource conservation, and hazardous material management. Lirn et al. (2013) evaluated the sustainability performance of three major Chinese container ports, focusing on air pollution, aesthetic and noise pollution, and waste and water pollution management. Dong et al. (2019) evaluated the environmental performance of ten major container ports in the Silk Road belt with greenhouse gas emission criteria and highlighted the significant impact of environmental performance on competitiveness and sustainable development. In addition to greenhouse gas emissions, Dovbischuk (2021) grouped climate change, resource efficiency, and biodiversity under environmental indicators. Asgari et al. (2015) included energy consumption as a critical indicator when measuring the sustainability performance of five UK ports. Laxe et al. (2017) used indicators such as education, land use efficiency, energy and water consumption, and waste recovery in their sustainability index, covering economic, institutional, environmental, and social factors.

The social dimension of sustainability is often neglected, leading to limited academic research on social sustainability in the maritime sector (Karakasnaki et al., 2023). However, Laxe et al. (2017) based their studies on commonly used social performance indicators, including employee numbers, training, gender equality, work accidents, and occupational health and safety. Majidi et al. (2021) considered social performance from the perspective of external stakeholders, evaluating it with indicators such as population, unemployment rate, and urbanization rate. Additional studies consider the port's distance from the city center (Kaya et al., 2023). Karakas et al. (2020) used the indicators of productive personnel ratio, labor turnover rate, and training hours per employee as a basis to evaluate corporate social performance. They found that the social dimension is the most important indicator after the logistics and operational dimensions.

Lim et al. (2019) note the widespread use of Multi-Criteria Decision Making (MCDM) methods in evaluating port sustainability performance, as these methods help clarify the relationships between various port characteristics like geography, legislation, size, and cargo types. The most commonly used MCDM method in the literature is AHP (Asgari et al., 2015; Wang et al., 2021). Data Envelopment Analysis (DEA) is also frequently used to evaluate port performance (Danladi et al., 2024; Li et al., 2022). Other MCDM methods used in sector studies include WASPAS (Kaya et al., 2023), ANP (Karakas et al., 2020), TOPSIS (Çelik and Yorulmaz, 2023; Acer and Yangınlar, 2017; Akandere, 2021), PROMETHEE (Stanković et al., 2021), SWARA, MARCOS, CoCoSo (Majidi et al., 2021), OCRA, and EATWOS (Görçün, 2021; Yüksekyıldız, 2021).

Turkish ports play a crucial role in the country's economy (TURKLİM, 2023; 7). Surrounded by seas on three sides and strategically located, Türkiye's port performance is vital for maintaining competitiveness in foreign trade (Çelik and Yorulmaz, 2023). The literature includes various studies on Turkish ports and their performance. Görçün (2021) examined the operational performance of nine Black Sea container ports, including Trabzon and Samsun, using indicators such as the number of employees, quay length and depth, equipment number, storage area, port area, handling capacity, and container volume (OCRA and EATWOS). Yüksekyıldız (2021) evaluated the efficiency of twenty Turkish container ports using similar indicators (EATWOS and ENTROPY). Baştuğ (2023) assessed the operational efficiency of twenty-three TURKLİM member port companies (DEA-SCOR), while Acer and Yangınlar (2017) evaluated twenty container ports (TOPSIS). Çelik and Yorulmaz (2023) assessed the performance of 13 container terminals, including Mersin Port, using indicators like handling capacity, port area, quay length and depth, and crane numbers (TOPSIS). Studies on the sustainability performance of Turkish ports are less common compared to operational performance studies. Kaya et al. (2023) evaluated (WASPAS) the sustainability performance of Marmara region container ports using thirty-six indicators grouped under economic, environmental, and social dimensions, finding that Marport and Asyaport had the highest performance. Akandere (2021) assessed the sustainability performance of five green-certified ports using data on emissions, electricity, and diesel consumption, container handling volume, port area, and equipment numbers from sustainability reports (2015-2018).

Table 1 presents the key indicators for assessing the operational, environmental, and social performance of container ports, with relevant references. As this study emphasizes operational activities over monetary outputs (Wang et al., 2024), the operational dimension is adopted instead of the economic dimension of sustainability.

Lim et al. (2019) emphasize that although the relevant literature is increasing, sustainability studies in maritime logistics remain limited compared to other logistics systems. This limitation is also evident in Türkiye, a country surrounded by seas on three sides. Although Karakas et al. (2020) developed a measurement model for the sustainability performance of container port facilities in the Marmara Sea, they did not evaluate port performance. Akandere (2021) assessed the environmental and operational performance of green-certified ports based on 2015-2018 data. Kaya et al. (2023) evaluated the sustainability of container ports in the Marmara region based on expert judgments rather than primary data. Consequently, this study aims to evaluate the operational, environmental, and social performance of container port facilities in different regions of Türkiye, using primary data from 2021-2022 years published by port facilities. Additionally, the study aims to determine the current status of sustainability orientations and approaches in Turkish container ports. In this respect, this study fills the gap in the literature by using primary data on port facilities in Türkiye and simultaneously evaluating the operational, environmental, and social performance dimensions of port facilities in an integrated manner. Using the MULTIMOORA method in evaluating the performance of ports also contributes to the literature in terms of method.

The research questions are:

- What are the general sustainability approaches of container port facilities (sustainability reporting systems, data recording, etc.)? What is the status of reporting environmental and social sustainability data?
- What sustainability-related documents/certificates do the facilities possess?
- What is the operational, environmental, and social performance status of container port facilities? Which facilities have the highest integrated (Environmental, Social, Operational-ESO) performance?
- Is there a parallel between the rankings of facilities' operational performance and their environmental and social performance?

Table 1. Performance indicators of port facilities

Performance	*Indicators*	*References*	*Unit*
Operational performance	Quay water depth	(Ding and Chou,2011)	meter
	Length of quay reserved for container	(Li et al.,2022)	meter
	Total port area	(Görçün,2021)	square meters
	Annual cargo throughput	(Iyer and Nanyam,2021b)	TEU (20 feet length for container)
	Container handling capacity	(Danladi et al.,2024)	TEU (annual)
Environmental performance	Emission release	(Dovbischuk,2021)	ton Carbon dioxide equivalents (CO_2e)
	Waste quantity	(Lirn et al.,2013)	ton
	Energy consumption	(Asgari et al.,2015)	gigajoule (GJ)
	Water consumption	(Roh et al.,2021;)	megaliter (ML)
Social performance	Percentage of female employees	(Stanković et al.,2021)	% (Number of female employees/total number of employees)
	Accident frequency rate	(Laxe et al.,2017)	% (every 1000000 hours)
	Training provided to employees	(Karakas et al.,2020)	hour/person

3. METHOD and DATA

3.1. Research Design and Method

Figure 1 provides an overview of the methodology used in line with the research purpose and problem. This study is descriptive in determining the current sustainability approaches and data of container port facilities in Türkiye and exploratory in evaluating the performance of these facilities.

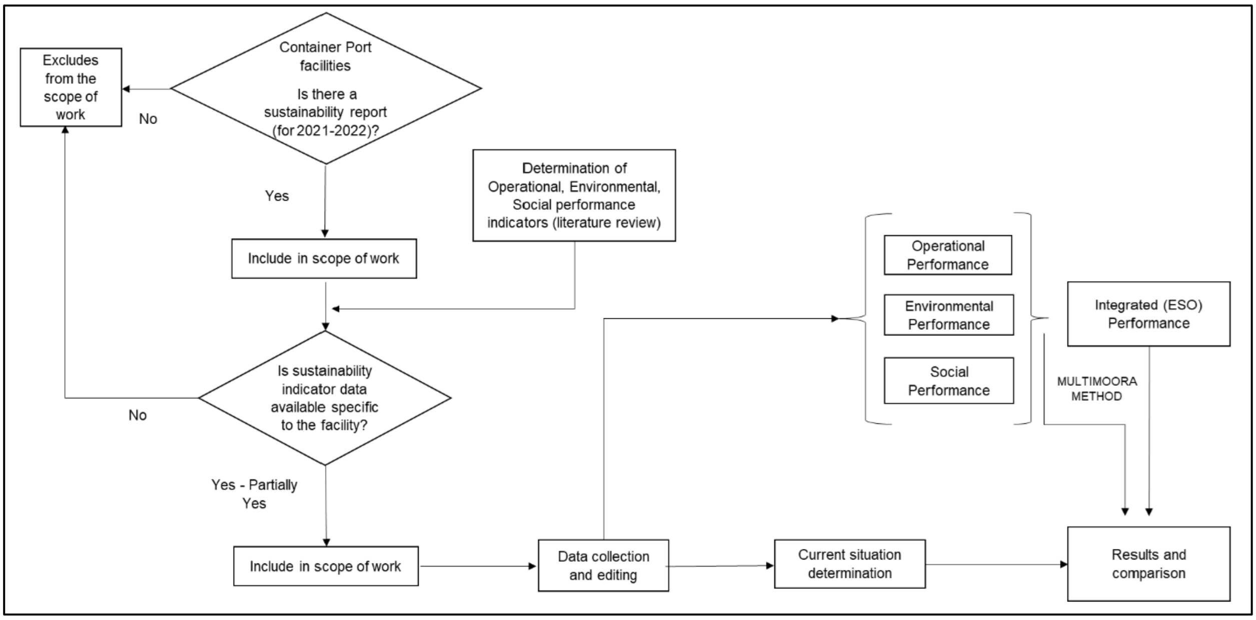

Figure 1. Design of the research

Performance indicators' literature reviews and container port facilities' sustainability reports have been conducted simultaneously. Data obtained from reports on indicators were analyzed using the MULTIMOORA method; performance rankings of port facilities were compared.

The multidimensional nature of sustainability in port facilities and the acquisition of data from various heterogeneous sources complicate decision-making (Stanković et al., 2021). Sustainability studies require a large number of performance indicators which are difficult to determine with different measurement units. Therefore, similar to the difficulty of measuring operational performance (Görçün, 2021), measuring environmental and social performance of sustainability is also an important challenge in the rational decision-making process (Lim et al., 2019). The maritime transport literature confirms the efficacy of multi-criteria decision-making (MCDM) methods, such as AHP, and PROMETHEE, for clearer problem formulation and informed decision-making (Majidi et al., 2021). However, no studies have evaluated the environmental, social and operational performance of container port facilities using the MULTIMOORA method, highlighting a gap this study aims to address.

The MULTIMOORA method (Multi-Objective Optimization by Ratio Analysis plus Full Multiplicative Form), developed by Brauers and Zavadskas (2013:72), is an MCDM method that integrates and evaluates multiple criteria, considering the interactions between them holistically. It has been extended by adding the Full Multiplicative Form to the Ratio System and Reference Point approaches of the MOORA (Multi-Objective Optimization Ratio Analysis) method (Hafezalkotob et al., 2019).

The MULTIMOORA Method’s Ratio System, as a fully compensatory model, is useful when “independent” criteria exist in the problem. For cases with “dependent” criteria, the Full Multiplicative Form, as an incompletely compensatory model, is beneficial. The Reference Point Approach, a non-compensatory model, is a conservative method compared to the Ratio System and Full Multiplicative Form. The Ratio System and Full Multiplicative Form allow for the compensation of poor performance on one criterion by better performance on other criteria, though the degree of compensation differs between the two techniques. In contrast, the Reference Point Approach does not permit such compensation. Since “dependent” and “independent” criteria may coexist in a problem, and to achieve a conservative result, MULTIMOORA integrates these three methods to leverage their respective advantages and attain a robust outcome (Hafezalkotob et al., 2019). The steps of the MULTIMOORA method are included in the following section (Brauers and Zavadskas, 2013; Hafezalkotob et al., 2019).

Step 1. Generate and normalization of the decision matrix: The first step in an MCDM problem is constructing a decision matrix and weight vector. Thus, for MULTIMOORA, the decision matrix composed of the ratings x_{ij} of m decision alternatives of the problem concerning n criteria is first constructed, as follows (Equation 1):

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{1}$$

The x_{ij} expression in the decision matrix shows the performance value of the ith alternative according to the jth criterion.

Because the ratings of alternatives on the multiple criteria of the problem may have different dimensions, the ratings should be normalized before utilization in an MCDM model. Regardless of whether the criteria in the decision problem are beneficial or non-beneficial, Equation 2 is used to normalize the decision matrix:

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

Step 2. Calculate the performance of decision alternatives using the Ratio System (RS) Approach: The performance values of non-beneficial criteria are subtracted from the sum of the performance values of the normalized beneficial-oriented criteria (Equation 3).

$$y_{ij}^* = \sum_{j=1}^{g} x_{ij}^* - \sum_{j=g+1}^{n} x_{ij}^* \tag{3}$$

Where g is the number of beneficial criteria and $(n-g)$ is the number of non-beneficial criteria. The best alternative based on the Ratio System has the maximum utility y_i and the ranking of this method is obtained in descending order (Equation 4):

$$R_{RS} = \{A_{i|max_i\ y_i} > \cdots > A_{i|min_i\ y_i}\} \tag{4}$$

Step 3. Calculate the performance of decision alternatives using the Reference Point (RPA) Approach: Based on the normalized data in Equation 1, the maximum value is determined as the reference point (r_i) if the decision alternatives are beneficial according to each criterion, and the minimum value is if they are not beneficial. The distances of the alternatives to the reference point according to each criterion are calculated with the help of Equation 5.

$$d_{ij} = \left| r_j - x_{ij}^{*} \right| \tag{5}$$

The score of the Reference Point Approach is obtained by maximizing the distance introduced in Equation 6.

$$z_i = max_j \, d_{ij} \tag{6}$$

The best alternative based on the Reference Point Approach has the minimum utility z_i. The ranking of the alternatives in ascending order is obtained by Equation 7.

$$R_{RPA} = \left\{ A_{i|min_i \; z_i} > \cdots > A_{i|max_i \; z_i} \right\} \tag{7}$$

Step 4. Calculate the performance of decision alternatives using the Full Multiplicative Form (FMF): To obtain the score of Full Multiplicative Form, the product of normalized alternatives ratings on beneficial criteria (A_i) is divided by the product of normalized alternatives ratings on non-beneficial criteria (B_i) (Equation 8-10).

$$U_i = \frac{A_i}{B_i} \tag{8}$$

$$\mathrm{A_i} = \prod_{\mathrm{g=1}}^{\mathrm{j}} \mathrm{x_{gj}} \,, \qquad i = 1,2, \ldots m \tag{9}$$

$$\mathrm{B_i} = \prod_{\mathrm{k=j+1}}^{\mathrm{n}} \mathrm{x_{ki}} \,, \qquad i = 1,2, \ldots m \tag{10}$$

The best alternative based on the Full Multiplicative Form has the maximum utility U_i and the ranking of this technique is generated in descending order (Equation 11).

$$R_{FMF} = \left\{ A_{i|max_i \; u_i} > \cdots > A_{i|min_i \; u_i} \right\} \tag{11}$$

Step 5. Ranking aggregation tools: Dominance Theory: In the MULTIMOORA method, Dominance Theory can be taken into account in combining the sub-rankings of the three approaches for the final ranking of the alternatives (Hafezalkotob et al., 2019). Detailed information about the dominance theory can be found in Brauers and Zavadskas (2013).

Ranking Position Method (RPM): This method is based on the $RPM\ (A_i)$ score for each alternative used to generate the final ranking. The score is calculated as follows (Equation 12) (Hafezalkotob et al., 2019):

$$RPM\ (A_i) = \frac{1}{\left(\frac{1}{r(y_i)} + \frac{1}{r(z_i)} + \frac{1}{r(u_i)}\right)} \tag{12}$$

Where $r(y_i)$, $r(z_i)$, $and\ r(u_i)$ are the rankings of Ratio System, Reference Point Approach, and Full Multiplicative Form, respectively, the best alternative based on the Rank Position Method has the minimum value of $RPM\ (A_i)$ (Hafezalkotob et al., 2019).

If the decision maker deems it necessary, the weight of the criteria (the importance coefficient) in the decision problem, that is, the importance coefficient (w_j), can be used in the MULTIMOORA method (Özbek, 2019; 198). However, in this study, which aims to determine the current situation, it is assumed that the criterion weights are equal.

3.2. Data Collection

This study aimed to obtain primary (qualitative and quantitative) data by examining reports and official documents, as well as the web pages of facilities, which serve as data sources in scientific research (Balaban Salı, 2012; 151). Sustainability reports are crucial tools businesses use to monitor the economic, environmental, and social impacts of their activities, providing a competitive advantage and sharing the results in a manner that meets stakeholders' demands. These reports, which reflect social responsibilities at the corporate level, are required by regulatory bodies, stock exchanges, and other financial institutions (Çalışkan, 2012). Therefore, to obtain the most reliable data on container port facilities whose performance is to be evaluated, it was essential to examine those facilities that have published sustainability reports, ensuring that their sustainability data and claims are genuine (ACCC, 2024).

The Ports Department Unit (www.tkygm.uab.gov.tr) under the Ministry of Transport and Infrastructure of the Republic of Türkiye oversees 46 coastal facilities permitted to service container ships and their cargo, including those with temporary operating permits. However, only 28 of these facilities are operational (Table 2) (TURKLİM, 2024: 103). It was investigated whether these facilities, which may be public, foreign, or public-foreign capital, published sustainability reports and the certificates and quality documents they had. The web pages of the facilities and their parent companies, if any, were scanned repeatedly. Data regarding 28 port facilities providing container services are presented in Table 2.

In the sustainability reports of the holdings to which some ports are affiliated, no specific data regarding the port facility itself were found (i.e., the port facility was not included in the holding's reporting scope) (Akçansa, Assan Port, DP World, Karasuport, Limaş, Mardaş). Therefore, these port facilities were excluded from the study. The study focused on port facilities that had a specific sustainability report (Asya Port, Evyapport, Kumport, MIP, QTerminals) and those included in the sustainability report of their parent holding (Borusan, Limak, Socar).

The most commonly used performance indicators in the literature for evaluating port facilities' performance are presented in Table 1 in the previous section. This study used six indicators for operational performance, four for environmental performance, and three for social performance. The sustainability reports of the included port facilities were re-examined, and relevant performance indicator data were collected. These data were cross-checked with information published on the websites of the Ministry of Transport and Infrastructure (www.uab.gov.tr) and TURKLİM (Turkish Port Operators Association) (www.turklim.org). The collected data were transferred to MS Excel 2016 tables and standardized into common units (Table 1). The performance indicator data of the port facilities are presented in Tables 3-5. Data collection occurred between 01.05.2024 and 10.07.2024.

4. RESULTS

4.1. Results of Sustainability Reporting

There are 28 container port facilities operating and licensed to provide services in Türkiye's Black Sea, Aegean, Marmara, and Mediterranean regions (TURKLİM, 2024). Of these, 14 port facilities (50%) have sustainability reports either within their organization or within the holding company they are affiliated with. Although the subsidiary holding companies have sustainability reports and mention sustainability on their corporate websites, six-port facilities (21%) are excluded from the holding company reports (Akçansa, Assan Port, DP World, Karasu Port, Limaş, Mardaş). Three ports (11%) included in the holding company sustainability report have facility-specific data: Borusan, Limak Port, and Socar Terminal. Additionally, five port facilities (18%) providing container services in Türkiye (Asya Port, Evyapport, Kumport, MIP, and Qterminals Akdeniz) have published facility-specific sustainability reports for either 2021 or 2022 (Asya Port and Evyapport lack a report for 2021; Qterminals lacks one for 2022).

All 28 container port facilities (100%) are within the scope of the ISPS (International Ship and Port Facility Security) code, which establishes mandatory security standards for international merchant ships and port facilities, enacted by the International Maritime Organization (IMO) in 2004 (Republic of Türkiye Ministry of Transport and Infrastructure, 2024). Two container ports in Türkiye, Asya Port and Marport, hold the Ecoport certificate issued by the European Sea Ports Organization (ESPO). Asya Port earned this with the PERS (The Port Environmental Review System) certificate, while Marport achieved it with ISO certification (www.ecoports.com). Under the "Green Port/Eco Port" project initiated by the Ministry of Transport and Infrastructure in Türkiye in 2014, 13 port facilities have green port certificates: Akçansa, Asya Port, Borusan, Evyapport, Kumport, Limaş, Limakport, Mardaş, Marport, Nemport, QTerminals, Samsunport, and Yılport (Akandere, 2021).

According to the "Green Port Report/Green Port Policy, Regulation and Applications" by TURKLIM (2013), ports with green port certificates must establish and document an integrated management system along with the ISO 9001 Quality Management System and ISO 14001 Environmental Management System. Consequently, container facilities with green port certificates, as listed in Table 2 (except Yılport data, which was inaccessible), also possess ISO 9001 and ISO 14001 certificates. Additionally, 19 port facilities have the ISO 9001 Quality Management System, 17 have the ISO 45001 Occupational Health and Safety Management System certificate, and 20 have the ISO 14001 Environmental Management System certificate. Furthermore, 36% of container port facilities in Türkiye have the ISO 50001 Energy Management System and 29% have the ISO 14064 Greenhouse Gas and Emissions Management System certificate.

The research accessed 13 sustainability reports (6 for 2021 and 7 for 2022) for eight port facilities. These reports were published in Turkish (Evyapport), English (Asya Port), and both Turkish and English (Borusan, Kumport, Limakport, MIP, Socar, QTerminals). Independent reports specific to the port facility range from 28 to 72 pages, while those within the holding range from 63 to 221 pages.

Table 2. Basic data on container port facilities with operating permits

	Conteiner port facilities	*City*	*Ownership structure*	*Sust.Reprt* 2021*	*Sust.Reprt* 2022*	*ISO9001*	*ISO45001*	*ISO14001*	*ISO27001*	*ISO50001*	*ISO14064*	*ISPS*	*GreenPort*	*EcoPort*	*Web address*
1	Akçansa Ambarlı	İstanbul	private (Turk-Foreign)(Sabancı-Heidelberg)												www.akcansa.com.tr
2	Assan Port	Hatay	private (Turk)(Kibar)												www.assanport.com.tr
3	Asya Port	Tekirdağ	private (Turk-Foreign)(Soyuer-MSC)												www.asyaport.com
4	Beldeport	Kocaeli	private (Turk)(Med.Lojistik)												www.beldeport.com.tr
5	Borusan	Bursa	private (Turk)(Borusan Holding)												www.borusanport.com/tr
6	Çelebi Bandırma	Balıkesir	private (Turk)(Çelebi OGG)												www.portofbandirma.com.tr
7	DP World	Kocaeli	private (Foreign)(DP World)												www.dpworld.com
8	Ege Gübre	İzmir	private (Turk)(Ege Gübre)												www.egegubre.com.tr
9	Evyaport	Kocaeli	private (Turk)(Evyap)												www.evyapport.com
10	Gemport (Yılport)	Bursa	private (Turk)(Yıldırım)												www.yilport.com
11	Haydarpaşa	İstanbul	public (TCDD)												www.tcdd.gov.tr
12	Karasuport	Sakarya	private (Turk)(IC)												www.karasuport.com.tr
13	Kumport	İstanbul	private (Foreign)(Fiba-COSCO Pasific)												www.kumport.com.tr
14	Limakport İskenderun	Hatay	private (Turk-Foreign)(Limak-Infrared)												www.limakports.com.tr
15	Limaş	Kocaeli	private (Turk)(Hayat)												www.limas.com.tr
16	Mardaş	İstanbul	private (Turk)(Hayat)												www.mardas.com.tr
17	Marport	İstanbul	private (Turk-Foreign)(Arkaş-TIL)												www.marport.com.tr
18	Mersin Int.Port (MIP)	Mersin	private (Turk-Foreign)(PSA-Akfen-IFM)												www.mersinport.com.tr
19	Nemport	İzmir	private (Turk)(Nemport A.Ş)												www.nemport.com.tr
20	Qterminals Akdeniz	Antalya	private (Turk-Foreign)(Subsidiary;Global Ports)												www.qterminals.com
21	Roda Port	Bursa	private (Turk)(Roda)												www.rodaport.com
22	Safiport Derince	Kocaeli	private (Turk)(Safi)												www.safiport.com.tr
23	Samsunport	Samsun	private (Turk)(Ceynak)												www.samsunport.com.tr
24	Socar Terminal	İzmir	private (Foreign)(SOCAR-Goldman Sachs)												www.socarterminal.com
25	TCDD İzmir	İzmir	public (TCDD)												www.tcdd.gov.tr
26	Trabzonport	Trabzon	private (Turk)(Albayrak)												www.trabzonport.com.tr
27	Ulusoy Çeşme	İzmir	private (Turk)(Ulusoy)												www.ulusoysealines.com
28	Yılport Gebze	Kocaeli	private (Turk)(Yıldırım)												www.yilport.com

Documents-certificates owned: ISO9001, ISO45001, ISO14001, ISO27001, ISO50001, ISO14064, ISPS, GreenPort, EcoPort

There is a facility-specific sustainability report.

There is no sustainability report specific to the facility.

The holding's sustainability report includes data specific to its facility.

Although the holding company has a sustainability report, facility-specific data is not included.

The facility has the relevant document.

*: Sustainable Report

Table 3. Operational performance indicator data of container port facilities

Port Facilities	*Quay water depth (meter)*	*Length of quay reserved for container* (meter)*	*Total port area (square meters)*	*Container handling capacity (TEU)*	*Annual cargo throughput (TEU)*		*The capacity utilization rate*	
					2021	*2022*	*2021*	*2022*
1 Asya Port	18	2010	300,000	2,500,000	1,802,517	1,796,876	0.72	0.72
2 Borusan	14.5	635	465,000	450,000	138,491	122,796	0.31	0.27
3 Evyapport	18.5	455	279,000	855,000	599,566	680,650	0.70	0.80
4 Kumport	16.5	2080	477,867	2,100,000	1,211,515	1,175,741	0.58	0.56
5 Limakport	15.5	920	1,000,000	1,000,000	476,627	496,583	0.48	0.50
6 MIP	15.8	1395	1,120,000	2,600,000	2,097,349	2,020,967	0.81	0.78
7 Socar	16	700	420,000	1,500,000	357,314	414,702	0.24	0.28
8 QTerminals	9.5	1117	203,920	350,000	116,786	93,016	0.33	0.27

(*) : Quay length is taken as the basis for container handling. This definition was not found for Asya Port and QTerminals.

Table 4. Environmental performance indicator data of container port facilities

	Emission release (Ton CO_2e)*		*Waste quantity** (Ton)*		*Energy consumption*** (GJ)*		*Water consumption (ML)*	
Port Facilities	*2021*	*2022*	*2021*	*2022*	*2021*	*2022*	*2021*	*2022*
1 Asya Port	-	15,089.0	-	-	72,931,163.1	80,628,934.5	-	-
2 Borusan	6,762.3	6,767.0	168.8	1,306.7	74,617.5	72,582.0	12.5	20.3
3 Evyapport	-	16,413.4	526.2	698.0	-	-	-	-
4 Kumport	13,052.8	32,969.4	268.8	244.8	1.3	1.3	22.5	25.5
5 Limakport	10,684.6	11,152.3	1,581.8	1,940.3	70,264.0	87,035.0	133.0	110.7
6 MIP	37,127.0	35,928.0	8,277.0	10,732.0	394,000.6	399,480.2	293.1	379.9
7 Socar	6,571.3	5,685.8	114.0	239.0	-	-	-	-
8 QTerminals	-	-	71.3	-	26,148.7	-	-	-

(*) : Based on Scope 1 and Scope 2 emission. Kumport included Scope 3 for 2022; Evyapport included Scope 3 and Scope 4.
(**): Total amount of hazardous and non-hazardous waste.(***): Total amount of electricity and other energy consumption.

Table 5. Social performance indicator data of port facilities

Port Facilities		*Percentage of female employees (%)*		*Accident frequency rate (for 1000000 hours)*		*Training provided to employees (hour/person)*	
		2021	*2022*	*2021*	*2022*	*2021*	*2022*
1	Asya Port	-	-	-	-	-	-
2	Borusan	-	-	2.01	11.11	-	-
3	Evyapport	-	0.073	-	-	-	48.15
4	Kumport	0.023	0.059	-	-	12.42	32.33
5	Limakport	0.088	0.089	6.17	5.17	-	-
6	MIP	0.060	0.060	7.89	6.83	-	-
7	Socar	0.098	0.101	2.10	4.67	66.50	31.53
8	QTerminals	-	-	6.60	-	-	-

The operational indicators (Table 1) for port facilities are comprehensively available in reports (Table 3). However, substantial gaps exist in the environmental indicator data (Table 4). Only four facilities—Borusan, Kumport, Limakport, and MIP—have consistently published complete environmental indicator data for both 2021 and 2022. Among the 13 sustainability reports examined, 8% lack data on emissions and waste, 17% lack data on energy consumption, and 38% lack data on water consumption. The specific missing environmental indicator data are as follows:

- *Emission Release*: QTerminals (2021)
- *Waste Quantity:* Asya Port (2022)
- *Energy Consumption:* Evyapport (2022); Socar (2021,2022)
- *Water Consumption:* Asya Port (2022); Evyapport (2022); Socar (2021,2022); QTerminals (2021)

Social performance data are also notably absent from many reports. Specifically, 31% of the accessible reports do not include data on the percentage of female employees or accident frequency rates, and 44% do not provide information on employee training. Socar is the only facility that reported all three social performance indicators (Table 5). The missing social performance data in the reports are as follows:

- *Percentage of Female Employees:* Asya Port (2022); Borusan (2021,2022); QTerminals (2021)
- *Accident Frequency Rate:* Asya Port (2022); Evyapport (2022); Kumport (2021,2022)
- *Employee Training:* Asya Port (2022); Borusan (2021, 2022); Limakport (2021,2022); MIP (2021, 2022); QTerminals (2021)

Notably, the 2021 reports for Evyapport and Asya Port and the 2022 report for QTerminals have not been published.

4.2. Performance Evaluation Results of Port Facilities

The subsequent section presents the results of the MULTIMOORA analysis (Equations 1-12), performed using MS Excel 2016, based on data collected from 13 reports about 8 port facilities included in the study.

4.2.1. Operational Performance

Iyer and Nanyam (2021b) emphasize that optimal capacity utilization is crucial in the global container market, which is subject to significant changes. The capacity utilization rate is defined as the ratio of theoretical capacity to actual production (Karanki and Bilotkach, 2023). Instead of treating annual container handled and annual handling capacity as separate indicators, this study calculated the capacity utilization rate to assess port performance. This approach aims to contribute to the literature by evaluating port performance using the "capacity utilization rate" indicator.

According to the operational performance indicator data of port facilities (Table 3), Evyap Port and Asya Port have the highest quay water depths, while Kumport and Asyaport possess the longest container quay. MIP port facility boasts the largest port area and the highest annual container handling capacity, achieving a high capacity utilization rate of 81% in 2021. In 2022, Evyapport achieved the highest capacity utilization rate at 80%. Notably, Evyapport, Limakport, and Socar showed an increase in capacity utilization rates compared to the previous year. MIP handled the most cargo in Türkiye during both periods.

The operational performance of the facilities was assessed using four indicators: quay water depth, length of quay reserved for containers, total port area, and container handling capacity utilization rate. All operational performance indicators are benefical (max). Therefore, Equation 8 in the Full Multiplicative Approach becomes invalid and the MULTIMOORA method turns into the MOORA method (Hafezalkotob et al., 2019). Therefore, the results of operational performance are obtained using the Ratio Approach and Reference Point Approach of the MOORA method. The operational performance ranking of port facilities for 2021 and 2022 is provided in Table 6. The Rank Position Method (RPM) (Hafezalkotob et al., 2019) was used for the final performance ranking of port facilities, with the facility having the smallest RPM value indicating the highest performance.

Table 6. Operational performance results for 2021 and 2022

Container Port Facilities	2021 RS (y_i^*)	R_{RS}	RPA (z_i)	R_{RPA}	RPM	2022 RS (y_i^*)	R_{RS}	RPA (z_i)	R_{RPA}	RPM
MIP	714739.23	1	647.69	1	0.5	714739.20	1	647.69	1	0.5
Limakport	569594.66	2	144844.88	2	1.0	569594.67	2	144844.88	2	1.0
Kumport	131200.52	3	584186.71	3	1.5	131200.50	3	584186.71	3	1.5
Borusan	123224.11	4	591094.10	4	2.0	123224.09	4	591094.10	4	2.0
Socar	100574.01	5	613768.81	5	2.5	100574.02	5	613768.81	5	2.5
Asya Port	52349.19	6	662961.41	6	3.0	52349.19	6	662961.41	6	3.0
Evyapport	44383.78	7	669884.25	7	3.5	44383.87	7	669884.25	7	3.5
QTerminals	24017.44	8	690527.85	8	4.0	24017.42	8	690527.85	8	4.0

RS: Ratio System Approach, RPM: Reference Point Approach, RPM: Score of Ranking Position Method, y_i^*: Score of Ratio system, z_i: Score of Reference Point Approach, R_{RS}, R_{RPA}: Rank

Since all indicator data in the operational performance evaluation, except for the capacity utilization rate, about the physical characteristics of the port, the performance values of the facilities were very similar, resulting in consistent performance rankings across both periods. According to the analysis, MIP emerged as the port facility with the highest operational performance (RPM=0.5). Limakport and Kumport also ranked among the top three in operational performance. Conversely, QTerminals demonstrated the lowest operational performance (RPM=4.0).

4.2.2. Environmental Performance

According to the environmental indicator data of port facilities (Table 4), MIP recorded the highest amounts of emissions, waste, energy, and water consumption for both periods. Conversely, Socar exhibited the lowest amounts of emissions and waste for both periods. Due to incomplete data, only four port facilities (Kumport, Borusan, Limakport, MIP) with comprehensive environmental indicator data were included in the analysis. The environmental performance indicators are non-beneficial (minimum). Therefore, Equation 8 in the Full Multiplicative Approach becomes invalid and the MULTIMOORA method is transformed into the MOORA method (Hafezalkotob et al., 2019). In fact, the results were obtained using the Ratio Approach and Reference Point Approach of the MOORA method. The environmental performance ranking of container port facilities for the years 2021 and 2022 is given in Table 7.

Table 7. Environmental performance results for 2021 and 2022

Container Port Facilities	2021 RS (y_i^*)	R_{RS}	RPA (z_i)	R_{RPA}	RPM	2022 RS (y_i^*)	R_{RS}	RPA (z_i)	R_{RPA}	RPM
Kumport	-4131.8	1	3015.4	1	0,5	-21080.0	2	12686.9	1	0.7
Borusan	-14786.3	2	13676.2	3	1,2	-13750.5	1	20626.8	3	0.8
Limakport	-15240.2	3	12126.9	2	1,2	-21541.1	3	18424.5	2	1.2
MIP	-423046.9	4	381310.3	4	2,0	-420733.6	4	384314.7	4	2.0

RS: Ratio System Approach, RPM: Reference Point Approach, RPM: Score of Ranking Position Method, y_i^*: Score of Ratio system, z_i: Score of Reference Point Approach, R_{RS}, R_{RPA}: Rank

The port facility with the highest environmental performance for both periods is Kumport (RPM=0.5 for 2021 and 0.7 for 2022). It is followed by the Borusan and Limakport facilities. Notably, Borusan's environmental performance improved in 2022 (RPM=0.8) compared to Limakport (RPM=1.2). MIP ranked lowest in environmental performance for both 2021 (RPM=2.0) and 2022 (RPM=2.0).

4.2.3. Social Performance

In terms of gender equality, Socar exhibits a high female-employee ratio (0.098 for 2021; 0.101 for 2022), whereas Kumport ranks lowest for both periods (0.023 for 2021; 0.059 for 2022). According to the United Nations' Review of Maritime Transport (2023; 102), the participation rate of female employees in the port industry remains low, with minimal changes over the years. Regarding accident frequency rates, Borusan had the highest performance in 2021 (2.01), while Socar achieved the top ranking in 2022 (4.67). MIP had the highest accident frequency rate in 2021 (7.89), and Borusan in 2022 (11.11). In terms of employee training, Socar provided the most training in 2021 (66.50 hours per person), but Evyapport surpassed it in 2022 with 48.15 hours per person. Despite MIP's leading operational performance (Table 6), it significantly underperforms in social performance indicators.

As only one facility, Socar reported all social performance indicator data, so a MULTIMOORA analysis for social performance was not conducted. The subsequent section will incorporate social performance into the integrated (ESO) performance evaluation of port facilities.

4.3.3. Integrated (Environmental, Social, Operational - ESO) Performance

In this section, the results of the integrated (ESO) performance assessment are presented by bringing together operational, environmental and social performance indicators for port facilities.

Due to substantial gaps in published data, particularly concerning environmental and social performance indicators, the number of indicators was reduced to ensure that a sufficient number of facilities could be evaluated. While a broader range of indicators could have been included, such an expansion would increase the dimensional complexity of the study. Consequently, the study adhered to the principles of completeness and minimum indicator conditions (Tzeng and Huang, 2011; 144) in selecting the indicators. The operational performance indicators selected are the length of the quay allocated for container service and the capacity utilization rate. For environmental performance, the amount of emission release and waste were chosen, while the accident frequency rate was the sole social performance indicator included. The MULTIMOORA analysis was conducted for four port facilities with available data (Borusan, Limakport, Socar, MIP). The length of the quay allocated for container service and the capacity utilization rate are considered beneficial (max), while the amount of emission release, waste, and accident frequency rate are considered non-beneficial (min). The results of the Ratio Approach, Reference Point Approach, and Full Multiplication Approach of the MULTIMOORA method, along with the RPM rankings, are presented in Table 8 (for 2021) and Table 9 (for 2022).

Table 8. Integrated (ESO) performance results for 2021

Container	*RS*		*RPA*		*FMF*		
Port Facilities	(y_i^*)	R_{RS}	(z_i)	R_{RPA}	(U_i)	R_{FMF}	*RPM*
Socar	-832.5	1	758.4	1	0.020	1	0.3
Borusan	-943.5	2	803.6	2	0.013	2	0.7
Limakport	-2730.1	3	1784.8	3	0.000	3	1.0
MIP	-41780.6	4	33575.6	4	0.000	4	1.3

RS: Ratio System Approach, RPM: Reference Point Approach, FMF: *Full Multiplicative Form,* RPM: Score of Ranking Position Method, y_i^*: Score of Ratio system, z_i: Score of Reference Point Approach, U_i: Score of Full Multiplicative Form, R_{RS}, R_{RPA}: Rank

Table 9. Integrated (ESO) results for 2022

Container	*RS*		*RPA*		*FMF*		
Port Facilities	(y_i^*)	R_{RS}	(z_i)	R_{RPA}	(U_i)	R_{FMF}	*RPM*
Socar	-587.9	1	758.4	1	0.003038	1	0.3
Borusan	-1138.6	2	803.6	2	0.000055	2	0.7
Limakport	-3121.8	3	2381.9	3	0.000010	3	1.0
MIP	-42875.6	4	32566.8	4	0.000001	4	1.3

RS: Ratio System Approach, RPM: Reference Point Approach, FMF: *Full Multiplicative Form,* RPM: Score of Ranking Position Method, y_i^*: Score of Ratio system, z_i: Score of Reference Point Approach, U_i: Score of Full Multiplicative Form, R_{RS}, R_{RPA}: Rank

The integrated (ESO) performance ranking of port facilities remained unchanged for both 2021 and 2022 (Table 9). The facility with the highest performance is Socar (RPM=0.3), followed by Borusan (RPM=0.7) and Limakport (RPM=1.0). MIP is ranked lowest in integrated (ESO) performance for both periods with an RPM of 1.3.

5. DISCUSSION and CONCLUSION

According to the research results examining the sustainability approaches and performance of container port facilities operating in Türkiye, only 18% of the facilities have independent sustainability reports. This is an improvement from the 13% reported by Piecyk and Bjorklund (2015) for logistics service providers. However, Hossain et al. (2021) found that 67% of European and 50% of North American ports prepare such reports. Given the proximity of Turkish ports to city centers and their importance in international trade (Yorulmaz and Patruna, 2022), expanding sustainability reporting is crucial. This finding, as indicated by Ashrafi et al. (2019), suggests that although sustainability is deemed important in port facilities, it is not adequately embraced in practice. Thus, sustainability efforts in Turkish ports are still nascent. Publishing a sustainability report is generally voluntary for companies; however, since it demonstrates the company's desire to be a good corporate citizen (Piecyk and Bjorklund, 2015), it is hoped that awareness of the role of port facilities in Türkiye in improving their global image will be increased.

46% of container port facilities have the Green Port certificate from the Ministry of Transport and Infrastructure. Increasing investments and incentives for this project can enhance economic development. 71% of facilities hold ISO 14001 certification, surpassing Hossain et al. (2021)'s 53%. However, it is important to note that different environmental certification programs such as PERS (Port Environmental Review System) and EMAS (Eco-Management and Audit Scheme) are also used in Europe and North America. Additionally, there is low interest in ISO 50001-Energy Management System and ISO 14064-Greenhouse Gas and Emissions Management System certification in the facilities. However, environmental certification initiatives of ports not only reduce negative environmental impacts but also improve economic performance and increase international competitiveness (Piecyk ve Bjorklund, 2015); thus, incorporating them into a corporate strategy for more ports could facilitate the international competitiveness of Turkish ports.

Port facilities in Türkiye include all operational data in sustainability reports due to the Ministry of Transport and Infrastructure's (2022) regulations. However, the lack of standardization in environmental and social performance data, which leads to inconsistencies in reporting, is one of the most important findings of this study. Piecyk and Björklund (2015) support the uncertainty regarding which aspects of sustainability are emphasized in the reports of companies providing logistics services. This indicates a need for enhanced efforts and regulations to improve the environmental and social dimensions of sustainability. Such improvements would advance sustainability initiatives for individuals, local administrations, and governments.

Recent studies on Turkish container ports consistently find MIP to have the highest operational performance due to its large area and high capacity utilization. Conversely, QTerminals has the lowest operational performance, showing a declining trend in efficiency according to Baştuğ (2023). Environmental performance rankings vary, with MIP ranking last in 2021 and 2022. Interestingly, Kumport and Borusan, lower in operational performance, top the environmental performance rankings, indicating a greater focus on environmental factors. Socar and Borusan lead in operational, environmental, and social dimensions, with Borusan's performance supported by Kaya et al. (2023). MIP ranks lowest in integrated (ESO) performance for both periods. These variations in performance highlight the need for further research on the strategies, policies, and decision-making mechanisms of each facility.

This study emphasizes the importance of evaluating the operational, environmental and social performance dimensions of ports in a integrated manner. Using publicly available data rather than subjective expert opinions ensures more objective results. The findings provide essential feedback for port management and help identify strengths and weaknesses in operational, environmental, and social performance. This can guide facility strategies and decision-making processes. Additionally, the study raises awareness among governments about sustainability policies and incentives. By employing the MULTIMOORA method, this research offers a practical and effective tool for performance evaluation, contributing to the literature and serving as a valuable decision-making resource for managers and policymakers.

This research is limited to Turkish container port facilities with published sustainability reports or data for 2021-2022, due to the unavailability of 2023 reports. The study assumes equal importance for all evaluation indicators. Future research could explore:

- In-depth investigations into challenges in sustainability reporting for Turkish container ports.
- Evaluating the performance of Turkish container port facilities by accessing all performance data; and comparing the results globally.
- Incorporation of indicator importance levels set by policymakers into performance analyses.
- Comparison of MULTIMOORA results with other methods to assess its effectiveness.
- Examining and comparing holistic sustainability performance across different port facility categories, including financial indicators.

Conflict of Interest
No potential conflict of interest was declared by the author.

Funding
Any specific grant has not been received from funding agencies in the public, commercial, or not-for-profit sectors.

Compliance with Ethical Standards
It was declared by the author that the tools and methods used in the study do not require the permission of the Ethics Committee.

Ethical Statement
It was declared by the author that scientific and ethical principles have been followed in this study and all the sources used have been properly cited.

REFERENCES

AAPA (American Association of Port Authorities), (2007). “D-11: Embracing the Concept of Sustainability as a Standard Practice for Ports and the Association”, www.aapa.files.cms-plus.com/PDFs/sustainability_resolutions.pdf, (Accessed: 09.06.2024).

ACCC (Australia Competition and Consumer Commission), (2024). “Environmental and Sustainability Claims”, www.accc.gov.au/business/advertising-and-promotions/environmental-and-sustainability-claims, (Accessed: 20.05.2024).

Acer, A. and Yangınlar, G. (2017). “The Determination of Turkish Container Ports Performance with TOPSIS Multiple Criteria Decision Making Method”, *Journal of Management Marketing and Logistics*, 4(2), 67-75.

Akandere, G. (2021). “Yeşil Sertifikali Limanlarin Performansinin Entegre ENTROPI-TOPSIS Yöntemleri ile Değerlendirilmesi”, Hacettepe University Journal of Economics and Administrative Sciences, 39(4), 515-535.

Akkan, M.M. (2022). “Türkiye’de Denizyolu Taşımacılığının Performansını Etkileyen Faktörlerin Ağırlıklandırılmasına Yönelik Bir Analiz”, *Konşimento Dergisi*, 1(1), 41-62.

Asgari, N., Hassani, A., Jones, D. and Nguye, H.H. (2015). “Sustainability Ranking of the UK Major Ports: Methodology and Case Study”, *Transportation Research Part E: Logistics and Transportation Review*, 78, 19-39.

Ashrafi, M., Acciaro, M., Walker, T.R., Magnan, G.M. and Adams, M. (2019). “Corporate Sustainability in Canadian and US Maritime Ports”, *Journal of Cleaner Production*, 220, 386-397.

Balaban Salı, J. (2018). “Verilerin Toplanması”, *Sosyal Bilimlerde Araştırma Yöntemleri,* (Editör: A. Şimşek), Anadolu Üniversitesi Yayını, Eskişehir, 134-161.

Baştuğ, S. (2023). “Port Efficiency Evaluation of Turkish Container Ports Based on DEA-SCOR Model: An Effective Sea Gateways in Türkiye for One Belt and One Road Initiative”, *Marine Science and Technology Bulletin*, 12(1), 27-38.

Bergantino, A.S., Musso, E. and Porcelli, F. (2013). “Port Management Performance and Contextual Variables: which Relationship? Methodological and Empirical Issues”, *Research in Transportation Business and Management*, 8, 39-49.

Bourne, M., Neely, A., Mills, J. and Platts, K. (2003). “Implementing Performance Measurement Systems: A Literature Review”, *International Journal of Business Performance Management*, 5(1), 1-24.

Brauers, W.K. and Zavadskas, E.K. (2013). “Multi-Objective Decision Making with a Large Number of Objectives. An Application for Europe 2020”, *International Journal of Operations Research*, 10(2), 67-79.

Çalışkan, A.Ö. (2012). “Sürdürülebilirlik Raporlaması”, *Journal of Accounting and Taxation Studies*, 5(1), 41-68.

Çelik, Y. and Yorulmaz, M. (2023). “Türkiye’deki Konteyner Terminallerinin Performans İncelemesi ve Mersin Limanı için Performans Gelişim Önerileri”, *Journal of Turkish Operations Management*, 7(1), 1531-1549.

Danladi, C., Tuck, S., Tziogkidis, P., Tang, L. and Okorie, C. (2024). “Efficiency Analysis and Benchmarking of Container Ports Operating in Lower-Middle-Income Countries: A DEA Approach”, *Journal of Shipping and Trade*, 9(1),7.

De Souza Barbosa, A., Da Silva, M.C.B.C., Da Silva, L.B., Morioka, S.N. and De Souza, V.F. (2023). “Integration of Environmental, Social, and Governance (ESG) criteria: Their Impacts on Corporate Sustainability Performance”, *Humanities and Social Sciences Communications*, 10(1), 1-18.

Ding, J.F. and Chou, C.C. (2011). “A Fuzzy MCDM Model of Service Performance for Container Ports”, *Scientific Research and Essays*, 6(3), 559-566.

Dong, G., Zhu, J., Li, J., Wang, H. and Gajpal, Y. (2019). “Evaluating the Environmental Performance and Operational Efficiency of Container Ports: an Application to the Maritime Silk Road”, *International Journal of Environmental Research and Public Health,* 16(12), 2226.

Dovbischuk, I. (2021). “Sustainable Firm Performance of Logistics Service Providers along Maritime Supply Chain”, *Sustainability*, 13(14), 8040.

Duong, N. H. (2022). “Relationship of Social Sustainability, Operational Performance and Economic Performance in Sustainable Supply Chain Management”, *Global Business & Finance Review*, 27(4), 46.

ESPO (European Sea Ports Organisation) (2023). “Environmental Report-EcoPortsinSights”, www.espo.be/media/ESPO%20Environmental%20Report%202023.pdf, (Accessed: 08.07.2024).

Ecoports network (2024). https://www.ecoports.com/network, (Accessed: 08.07.2024).

Görçün, Ö.F. (2021). “Efficiency Analysis of Black Sea Container Seaports: Application of an Integrated MCDM Approach”, *Maritime Policy and Management*, 48(5), 672-699.

Hafezalkotob, A., Hafezalkotob, A., Liao, H. and Herrera, F. (2019). “An Overview of MULTIMOORA for Multi-Criteria Decision-Making: Theory, Developments, Applications and Challenges”, *Information Fusion*, 51, 145-177.

Hossain, T., Adams, M. and Walker, T.R. (2021). “Role of Sustainability in Global Seaports”. *Ocean and Coastal Management*, 202, 105435.

Humphreys, R.M. (2023). “Why Ports Matter for the Global Economy”, www.blogs.worldbank.org/en/transport/why-ports-matter-global-economy (Accessed: 20.06.2024).

Iyer, K.C. and Nanyam, V.P.S.N. (2021a). “A Grounded Theory Approach in the Identification of Enabling and Inhibiting Factors Affecting the Performance of Container Terminals”, *Transportation in Developing Economies,* 7, 24.

Iyer, K.C. and Nanyam, V.N. (2021b). “Technical Efficiency Analysis of Container Terminals in India”, *The Asian Journal of Shipping and Logistics*, 37(1), 61-72.

Karakas, S., Acar, A.Z. and Kirmizi, M. (2020). “Development of a Multidimensional Performance Evaluation Model for Container Terminals at Marmara Sea”, *Research in Transportation Business-Management*, 37, 100498.

Karakasnaki, M., Pantouvakis, A. and Vlachos, I. (2023). “Maritime Social Sustainability: Conceptualization and Scale Development”, *Transportation Research Part D: Transport and Environment*, *121*, 103804.

Karanki, F. and Bilotkach, V. (2023). "Capacity Utilization of U.S. Airports: A Data Envelopment Analysis", *Transportation Research Part A: Policy and Practice,* 177, 103840.

Kaya, S.K., Kundu, P. and Görçün, Ö.F. (2023). “Evaluation of Container Port Sustainability Using WASPAS Technique Using on Type-2 Neutrosophic Fuzzy Numbers”, *Marine Pollution Bulletin*, 190, 114849.

Klassen, R.D. and McLaughlin, C.P. (1996). “The Impact of Environmental Management on Firm Performance”, *Management Science,* 42(8), 1199-1214.

Laxe, F.G., Bermúdez, F.M., Palmero, F.M. and Novo-Corti, I. (2017). “Assessment of Port Sustainability Through Synthetic Indexe, Application to the Spanish Case”, *Marine Pollution Bulletin*, 119(1), 220-225.

Li, Z., Wang, X., Zheng, R., Na, S. and Liu, C. (2022). “Evaluation Analysis of the Operational Efficiency and Total Factor Productivity of Container Terminals in China”, *Sustainability,* 14(20).

Lim, S., Pettit, S., Abouarghoub, W. and Beresford, A. (2019). “Port Sustainability and Performance: A Systematic Literature Review”, *Transportation Research Part D: Transport and Environment*, *72*, 47-64.

Lirn, T.C., Jim Wu, Y.C. and Chen, Y.J. (2013). “Green Performance Criteria for Sustainable Ports in Asia”, *International Journal of Physical Distribution and Logistics Management*, 43(5/6), 427-451.

Majidi A., Mirzapour Al-e-Hashem, S.M.J. and Hashemkhani Zolfani, S. (2021). “Sustainability Ranking of the Iranian Major Ports by Using MCDM Methods”, *Mathematics,* 9(19), 2451.

Mangla, S.K., Kusi-Sarpong, S., Luthra, S., Bai, C., Jakhar, S. K. and Khan, S. A. (2020). “Operational Excellence for Improving Sustainable Supply Chain Performance”, *Resources, Conservation and Recycling*, 162, 105025.

Nanyam, V.N. and Jha, K.N. (2022). “Operational Performance Model for Indian Container Terminals Using Qualitative Comparative Analysis”, *The Asian Journal of Shipping and Logistics*, 38(4), 197-206.

Notteboom, T.E., Satta, G., Persico, L., Vottero, B. and Rossi, A. (2023). “Operational Productivity and Financial Performance of Pure Transhipment Hubs versus Gateway Terminals: An Empirical Investigation on Italian Container Ports”, *Research in Transportation Business & Management,* 47, 1-15.

Özbek, A. (2019). “Çok Kriterli Karar Verme Yöntemleri ve Excel İle Problem Çözümü-Kavram Teori Uygulama”, Seçkin Yayıncılık, Ankara.

Piecyk, M.I. and Björklund, M. (2015). “Logistics Service Providers and Corporate Social Responsibility: Sustainability Reporting in the Logistics Industry”, *International Journal of Physical Distribution and Logistics Management*, 45(5), 459-485.

Porter, M.E. (2003). “Corporate Philanthropy: Taking the High Ground”, Foundation Strategy Group. http://earthmind.net/ngo/docs/philanthropy-high-ground.pdf, (Accessed: 02.07.2024)

Republic of Türkiye Ministry of Transport and Infrastructure. (2024). “İşletme İzinli Kıyı Tesislerine İlişkin Bilgiler”, www.tkygm.uab.gov.tr/limanlar-daire-baskanligi, (Accessed: 05.06.2024).

Republic of Türkiye Ministry of Transport and Infrastructure. (2022). “Kıyı Tesislerine İşletme İzni Verilmesine İlişkin Usul Ve Esaslar Hakkında Yönetmelik**”,** www.mevzuat.gov.tr/MevzuatMetin/yonetmelik/7.5.40082.pdf, (Accessed: 29.06.2024).

Roh S., Thai V.V., Jang H. and Yeo G.T. (2021). “The Best Practices of Port Sustainable Development: A Case Study in Korea”, *Maritime Policy & Management*, 1-27.

Sheikh, W., Chowdhury, M.M.H. and Mahmud, K.K. (2023). “A Comprehensive Performance Measurement Model for Maritime Logistics: Sustainability and Policy Approach”. *Case Studies on Transport Policy,* 14, 101097.

Stanković, J.J., Marjanović, I., Papathanasiou, J. and Drezgić, S. (2021). “Social, Economic and Environmental Sustainability of Port Regions: MCDM Approach in Composite Index Creation”, *Journal of Marine Science and Engineering*, 9(1), 74.

TURKLİM (Port Operators Association of Türkiye), (2024). “Türkiye Limancılık Sektörü 2024 Raporu-Limanlarda Dijital Teknolojiler ve Akıllı Limanlar”, www.turklim.org/turklim-sektor-raporu-2024/, (Accessed: 10.06.2024).

TURKLİM (Port Operators Association of Türkiye), (2013). “Yeşil Liman Raporu/Yeşil Liman Politika, Düzenleme ve Uygulamaları, Türkiye Limancılık Sektörü Raporu”, www.turklim.org/kport/yesil_liman/upload/YesilLiman-Turklim-Raporu.pdf, (Accessed: 21.03.2021).

Tzeng, G-H. and Huang, J.J. (2011). “Multiple Attribute Decision Making: Methods and Applications” (1st edition), Chapman and Hall/CRC.

United Nations (UN). (2023). “Review Of Maritime Transport: Towards a Towards a Green and just Green and just Transition”, Geneva, https://unctad.org/system/files/official-document/rmt2023_en.pdf, (Accessed: 01.07.2024).

UNCTAD (United Nations Trade and Development). (2024). “Review of Maritime Transport”, https://unctad.org/topic/transport-and-trade-logistics/review-of-maritime-transport, (Accessed: 10.07.2024).

Utikad (Turkish Forwarding and Logistics Association). (2023). “Denizyolunun Sürdürülebilir Büyümesinde Limanlar Başrolde”, www.utikad.org.tr/Detay/Sektor-Haberleri/35539/denizyolunun-surdurulebilir-buyumesinde-limanlar-basrolde, (Accessed: 18.06.2024).

Venus Lun, Y.H., Lai, K., Wong, C.W.Y. and Cheng, T.C.E. (2016). “Green Shipping Management”, Springer, London.

Vrakas, G., Chan, C. and Thai, V. V. (2021). “The Effects of Evolving Port Technology and Process Optimisation on Operational Performance: The Case Study of an Australian Container Terminal Operator”, *The Asian Journal of Shipping and Logistics*, 37(4), 281-290.

Wang, C., Haralambides, H. and Zhang, L. (2021). “Sustainable Port Development: The Role of Chinese Seaports in the 21st Century Maritime Silk Road”, *International Journal of Shipping and Transport Logistics*, 13(1-2), 205-232.

Wang, Z., Hu, H. and Zhen, L. (2024). “Berth and Quay Cranes Allocation Problem with On-Shore Power Supply Assignment in Container Terminals”, *Computers and Industrial Engineering,* 188, 109910.

Woo, SH., Pettit, S. and Beresford, A. (2011). “Port Evolution and Performance in Changing Logistics Environments”, *Maritime Economics & Logistics,* 13, 250-277.

Yüksekyıldız, E. (2021). “Entropi ve EATWOS Yöntemleri ile Türkiye Konteyner Limanlarının Verimlilik Analizi”, *Verimlilik Dergisi,* 2, 3-24.

Yorulmaz, M. and Baykan, Y. (2023). “Türkiye’de Sürdürülebilir Liman İşletmeciliği ve Yönetimi Literatürünün Değerlendirilmesi”, *Journal of Sustainable Environment,* 3(1), 1-12.

Yorulmaz, M. and Patruna, E. (2022). “Sürdürülebilir Yeşil Liman Algısının ve Yönetiminin Değerlendirilmesi”, *International Journal of Afro-Eurasian Research*, 7(13), 148-168.

VERİMLİLİK DERGİSİ
JOURNAL OF PRODUCTIVITY

A Model for Vehicle Routing Problem under Returns and Emission Consideration in B2C E-Commerce Logistics

Sedat Belbağ[1]

ABSTRACT

Purpose: With the widespread use of the Internet, electronic commerce allows customers to purchase products from the virtual stores of businesses instead of physical stores. This study addressed a mixed-integer linear programming model for a vehicle routing problem under returns and emission considerations in B2C e-commerce logistics.

***Methodology*:** This study proposes a mathematical model to solve a variant of the vehicle routing problem. The objective is to minimize the fuel consumption cost, penalty cost for unmet demand of returned items, and fixed cost for operating a vehicle. A clustering-based solution algorithm has been introduced to solve large-sized instances within reasonable solution times.

Findings: The numerical analysis for the base case shows that the suggested model can assist decision-makers in coordinating forward distribution and reverse collection decisions within the context of sustainable e-commerce logistics. The result of the adjusted model for minimizing emission shows that a reduction of nearly 17% in total emission amount can be achieved, however, the adjusted model postpones all demand for the collection of returned items. Furthermore, the cluster-based solution approach causes a considerable decrease in solution time while providing promising solutions.

Originality: This study represents a contribution to the existing literature on the subject by considering: i) emission to determine effects on the vehicle routing problem, ii) the postponement of the collection of returned items due to the limited delivery time, iii) proposing the clustering-based solution approach to tackle with larger-sized problems.

***Keywords*:** E-Commerce Logistics, Vehicle Routing Problem, Product Returns, Emission.

***JEL Codes*:** L91.

B2C E-Ticaret Lojistiğinde Geri Dönmüş Ürün ve Emisyonun Dikkate Alındığı Araç Rotalama Problemine İlişkin Bir Model

ÖZET

Amaç: Elektronik ticaret internet kullanımının yaygınlaşması ile birlikte müşterilerin ürünleri fiziksel mağazalar yerine işletmelerin sanal mağazalarından satın almasına olanak sağlamaktadır. Bu çalışmanın amacı, B2C e-ticaret lojistiğinde iade ve emisyon hususları altında bir araç rotalama problemi için bir karma tamsayılı doğrusal programlama modeli önermektir.

Yöntem: Bu çalışma, araç rotalama probleminin bir varyantını çözmek için bir matematiksel model önermektedir. Modelin amacı, yakıt tüketim maliyetini, iade edilen ürünlerin karşılanmayan talebi için ceza maliyetini ve bir aracın işletilmesi için sabit maliyeti en aza indirmektir. Büyük boyutlu örnekleri makul çözüm süreleri içinde çözmek için kümeleme tabanlı bir çözüm algoritması önerilmektedir.

Bulgular: Örnek olay analizi için yapılan sayısal analiz, önerilen modelin sürdürülebilir e-ticaret lojistiği bağlamında ileri yönlü dağıtım ve iade toplama kararlarının koordine edilmesinde karar vericilere yardımcı olabileceğini göstermektedir. Emisyonu en aza indirmeye yönelik düzenlenmiş modelin sonucu, toplam emisyon miktarında yaklaşık %17'lik bir azalma sağlanabileceğini göstermektedir, ancak düzenlenmiş model iade edilen ürünlerin toplanması için olan tüm talebi ertelemektedir. Ayrıca, küme tabanlı çözüm yaklaşımı umut verici çözümler sunarken çözüm süresinde önemli bir azalmaya neden olmaktadır.

Özgünlük: Bu çalışma, i) emisyonun araç rotalama problemi üzerindeki etkileri belirlenmesini, ii) sınırlı teslimat süresi nedeniyle iade edilen ürünlerin toplanmasının ertelenmesini, iii) daha büyük boyutlu problemlerle başa çıkmak için kümeleme tabanlı çözüm yaklaşımını önererek konuyla ilgili mevcut literatüre bir katkı sunmaktadır.

Anahtar kelimeler: E-Ticaret Lojistiği, Araç Rotalama Problemi, Geri Dönmüş Ürün, Emisyon.

JEL kodları: L91.

[1] Ankara Hacı Bayram Veli Üniversitesi, İktisadi ve İdari Bilimler Fakültesi, İşletme Bölümü, Ankara, Türkiye

Corresponding Author: Sedat Belbağ, sedat.belbag@hbv.edu.tr

DOI: 10.51551/verimlilik.1533127
Research Article | Submitted: 14.08.2024 | Accepted: 29.12.2024
Cite: Belbağ, S. (2025). "A Model for Vehicle Routing Problem under Returns and Emission Consideration in B2C E-Commerce Logistics", *Verimlilik Dergisi,* Productivity for Logistics (SI), 63-76.

1. INTRODUCTION

The e-commerce industry has experienced substantial growth alongside advancements in technology. European business-to-customer (B2C) e-commerce turnover increased to €958 billion in 2024 with 8% growth compared to the previous year (EuroCommerce, 2024: 7). A similar trend can also be observed in emerging markets such as India and China (Tiwari and Sharma, 2023; Li et al., 2021). As an emerging market, the transaction volume of e-commerce has increased to $77,89 billion in 2023 and is anticipated to be $82,39 billion at the end of 2024 in Türkiye (T.C. Ticaret Bakanlığı, 2023: 18). Along with advances in technology, unexpected outbreaks may also affect customer interest in e-commerce. For instance, the COVID-19 outbreak causes considerable changes in both the lifestyle and consumption habits of consumers (Kawasaki et al., 2022; Güngördü Belbağ, 2022). During the COVID-19 era, the increasing trend of e-commerce continues while other industries cope with the recession in the economy.

Globalization, increasing costs, and increasing competitiveness in national and international trade lead logistics companies to provide efficient and productive processes (Samut, 2023; Şahinaslan et al., 2023). The rapid surge in e-commerce sales has exerted considerable pressure on companies to fulfill orders, promptly. Consumers expect expedited and reliable delivery in e-commerce logistics services (Güngördü Belbağ, 2022). The distribution of products becomes a prominent process to meet or exceed customer expectations. Determining vehicle routes is getting more time-consuming and costly process in the e-commerce industry, especially for last-mile delivery operations. The final stage of the delivery process, known as the 'last mile', represents the costly and environmentally damaging aspect of online retail. It is the stage that requires the greatest input of energy and carbon, making it the most energy- and carbon-intensive part of the entire process. (UNCTAD, 2024: 2). Last-mile delivery has the greatest impact on the environment and is the most inefficient stage of the supply chain (OliverWyman, 2021; Mangiaracina et al., 2015; Ranieri et al., 2018). Last-mile delivery is the final part of the supply chain operations, which aims to transport products from local depots to final customers. While being the final phase of a B2C parcel distribution service, last-mile delivery substantially elevated traffic congestion in urban areas (Ranieri et al., 2018; Viu-Roig and Alvarez-Palau, 2020).

Compared to traditional sales, however, the ratio of returns in e-commerce sales is generally higher, approximately 35% of original orders (Meyer, 1999). High return rates impose additional complexity on the transportation process. The collection of returned products becomes an important issue within the limited time of transportation. Late or delayed collection of returned products may also dissatisfy customers. Many internet-based direct sales companies (e.g., Hepsiburada, Trendyol) deliver orders of new products and collect returns simultaneously with their vehicles. Thus, the route of vehicles should be reconsidered concerning additional customers with returned products.

The supply chain for e-commerce logistics has the potential to pose significant environmental risks, potentially affecting biodiversity, food and water security, and local livelihoods (UNCTAD, 2024: 12-13). Freight transportation is a major contributor to CO_2 emissions, which adversely affect human health and contribute to environmental degradation. For instance, freight transportation is accountable for 21% of CO_2 emissions within the transport sector in the United Kingdom. (McKinnon, 2007: 4). E-commerce, however, has the potential to reduce environmental impact compared to conventional shopping by consolidating multiple customer trips into efficient home delivery routes (Matthews et al., 2001). The design of efficient vehicle routes has the potential to result in a reduction in the total fuel consumption of these vehicles, as well as in emissions to the environment.

The present study makes a contribution to the existing literature on the subject as follows. First, there is limited research on the environmental impacts of e-commerce logistics (Mangiaracina et al., 2015). Therefore, this study considers emission as a sustainability concern to determine the effects on the vehicle routing problem. Thus, the present study also adheres to Sustainable Development Goal 13, which deals with climate change (United Nations, 2024a). United Nations (UNStats, 2019) highlights that it is vital to reduce global carbon emissions to 45% by 2030 and achieve net zero emissions by 2050. Even though carbon dioxide emissions intensity declined, it is insufficient, thus, the United Nations calls for developing strategies for low-carbon energy, and energy-efficient solutions (United Nations, 2024b). There are also other calls for research to provide solutions for reducing carbon emissions (Şahinaslan et al., 2023; Samut, 2023). This will allow low-carbon transformations and help to achieve the goal of the Paris Agreement in the long term (United Nations, 2023). Therefore, businesses need to reduce their environmental impacts by handling logistics, and returns (UNCTAD, 2024). Incorporating sustainability into logistics also supports the achievement of sustainable development goals (Samut, 2023). Second, the current study considers the postponement of returned products from customers, however, too many uncollected items have the potential to cause customer dissatisfaction with the company in e-commerce logistics. Third, the clustering-based solution approach has been introduced to solve large-sized instances within reasonable solution times.

This study provides a mathematical model (i.e., a mixed integer programming - MILP) for a vehicle routing problem under returns and emission considerations in B2C e-commerce logistics. The suggested model considers emission as a sustainability concern to determine effects on the vehicle routing problem and allowance of returned products from customers where uncollected items have the potential to cause customer dissatisfaction toward the company in e-commerce logistics. The numerical analyses highlight the benefits that can be achieved through the proposed model and solution approach.

The remainder of this paper is structured as follows. Section 2 provides a brief literature review on e-commerce logistics, green vehicle routing problem, and last-mile delivery and the contribution of the current study in detail. Section 3 describes the considered problem and explains the structure of the mathematical model. Section 4 introduces the clustering-based solution approach to solve larger-sized problems within short computational times. Section 5 presents the numerical analyses to demonstrate the applicability of the aforementioned model. Finally, Section 6 concludes the study by discussing its limitations and potential directions for future research.

2. LITERATURE REVIEW

In general, a VRP, which was first introduced by Dantzig and Ramser (1959), aims to minimize total costs while determining the optimal route of vehicles in transportation. VRP is the most common problem considered by many researchers in the logistics industry. Currently, a considerable number of studies consider the variants of the vehicle routing problem (VRP). The classic VRP can be extended to various VRP variants such as time-dependent VRP (Çimen and Soysal, 2017), VRP with pickup and delivery (Soysal et al., 2020), inventory routing problem (Soysal et al., 2021), pollution routing problem (Bektaş and Laporte, 2011), sustainable VRP (Dündar et al., 2021) and green VRP (Erdoğan and Miller-Hooks, 2012).

Green VRP is an extension of the classic routing problem and is concerned with the minimization of energy consumption through the adoption of alternative-fueled and/or hybrid electric vehicles into the vehicle pool. Although early papers were published before 2010 (Barth et al., 2005; Apaydin and Gonullu, 2008; Silva et al., 2009), the mainstream of routing problems related to pollution emissions and energy consumption have gained significant attention from researchers since 2010 and have become a critical issue in recent years. Research on Green-VRP typically focuses on optimizing energy consumption to mitigate pollution in logistics and transportation activities. Transportation, fuel or energy consumption, and pollution are the three main dimensions of the green VRP. Conventional fossil fuel-powered vehicles, alternative-fueled, and hybrid electric vehicles are considered by papers in green VRP literature. Conventional fossil fuel-powered vehicles produce a considerable amount of greenhouse gases in the transportation of goods. The pollution routing problem seeks to minimize fuel consumption and CO_2 emissions generated by conventional fossil fuel-powered vehicles. Bektaş and Laporte (2011) introduce a more comprehensive objective function that not only accounts for the distance traveled by vehicles but also incorporates the costs of travel time, fuel, and greenhouse gas (GHG) emissions. On the other hand, alternative-fuel powered vehicles provide greener energy sources like hydrogen, natural gas, electricity, etc. (Erdogan and Miller-Hooks, 2012). Electric vehicles are a common example of alternative-fuel powered vehicles; however, their range in transportation is limited by the storage capacity of their batteries. Unlike electric vehicles, hybrid electric vehicles do not suffer from range limitations. Hybrid electric vehicles can overcome this obstacle by switching between fuel and battery power based on requirements that help lessen the need for frequent stops and reliance on infrastructure (Mancini, 2017). As a result, hybrid electric vehicles can help reduce the use of fossil fuels on other trips, leading to a decrease in both costs and CO_2 emissions. Green VRP extends the economic objectives of traditional VRP (e.g., travel cost, fuel/charging cost) with environmental objectives (e.g., fuel consumption, emissions), and social objectives (e.g., satisfaction, working hours of drivers).

Traditional logistics aims to transport products from one business to another business (B2B) under predetermined conditions. On the other hand, e-commerce logistics has become an important option for companies with the introduction of the internet and internet-based technologies in the B2C environment. In today’s business environment, e-commerce logistics is defined as the backbone of e-commerce operations (Delfmann et al., 2002).

The e-commerce supply chain generally consists of three main stages: first-mile, middle-mile, and last-mile. First-mile and middle-mile logistics operations are usually related to the transportation of products from the business to the business environment. Last-mile logistics, however, is mainly responsible for the transportation of products from local distribution centers to customers in a short time. Last-mile delivery poses significant challenges and costs in e-commerce logistics due to the stringent demands of consumer service (Vanelslander et al., 2013; Seghezzi and Mangiaracina, 2021). For detailed literature reviews on e-commerce logistics, readers can see the studies of Al Mashalah et al. (2022) and Risberg (2023).

The growing number of transactions in e-commerce forces companies to deploy more vehicles to meet customer needs on time during last-mile delivery. The addition of conventional fossil fuel-powered vehicles not only increases transportation costs but also has a negative impact on the environment by emitting greenhouse gases. As the final stage of e-commerce logistics, last-mile delivery should prioritize the reduction of carbon emissions along with transportation costs and customer satisfaction (Yu et al., 2024).

To highlight the related literature, we conducted a search for articles indexed in the Web of Science (WOS) database using the keywords "*e-commerce*", "*vehicle routing"* and "last-mile" within the "*topic*" field. Among the results, seventeen studies were manually selected based on their scope and empirical relevance. Table 1 exhibits a synopsis of the related literature.

The brief literature review reveals that some studies (Li et al., 2013 and Li et al., 2021 - location routing problem; Ge et al., 2018 and Zuhanda et al. 2023 – two-echelon VRP) consider e-commerce logistics in both strategic and tactical levels. The rest of the studies consider the tactical level of e-commerce logistics with variants of VRP (e.g., Moons et al., 2019 - Integrated order picking VRP; Fonseca-Galindo et al., 2022 – Dynamic VRP). Furthermore, only three studies (Li et al., 2013; Li et al. 2021; Zhang et al., 2021) considered the reverse flow of products. Li et al. (2013) suggest a mathematical model for LIRP where forward and reverse demands should be met at the same time. It is assumed that the returned products are without any defect in quality. The model aims to minimize the total cost of forward and reverse logistics. Li et al. (2021) consider a location-routing problem under the integration of collection and distribution. The suggested multi-objective model aims to minimize total logistics costs and maximize customer satisfaction, simultaneously. Zhang et al. (2021) extend a similar problem by considering the time window, and multi-depot assumptions. The model aims to minimize total transportation costs and penalty costs for late delivery.

Many studies consider fuel consumption and emission in the last-mile delivery of e-commerce in recent years. Tiwari and Sharma (2023) investigate the effect of emissions on routing decisions by considering emission cost with a side constraint. Total emission cost should not be over the pre-determined budget at the end of the distribution process. Yu et al. (2024) consider a multi-objective model that minimizes transportation costs and carbon emissions and maximizes customer satisfaction to solve the last-mile delivery problem. The results show that the proposed algorithm decreases transportation cost, and carbon emission amount and provides higher customer satisfaction.

Some studies suggest establishing pickup points instead of delivering parcels directly to customer locations (e.g., Wang et al., 2022) or consolidating deliveries to reduce the number of vehicles used (e.g., Muñoz-Villamizar, 2022), aiming to decrease fuel consumption and emissions. The studies that consider pickup points in last-mile delivery include Heshmati et al. (2019), Wang et al. (2022), and Wehbi et al. (2022). Heshmati et al. (2019) investigate various e-commerce delivery scenarios such as the impact of electric bicycles and cars, aggregated collection points, carrier bundling, and changing delivery times to minimize emission and routing costs. The results of the study show that delivering parcels to a collection point instead of home delivery provides a decrease in both transportation costs and the amount of emission. Wang et al. (2022) addressed a location-routing problem where the selection of pickup locations and delivery plans of green vehicles (i.e., electric vehicles) are optimized simultaneously. It has been noted that the branch & price algorithm suggested to solve the problem produces superior outcomes compared to commercial branch-and-cut solvers. Wehbi et al. (2022) present a study that introduces a model for a vehicle routing problem with portering (VRP-P) with time windows, which combines the use of on-foot porters and cargo vans in the delivery process. The model simultaneously determines both the vehicle routes and porter paths where a porter meets the vehicle at a handover point. The computational results of the study demonstrate that utilizing porters is advantageous, leading to up to a 50% reduction in journey times.

The studies that consider the consolidation of deliveries to reduce the number of vehicles used are Muñoz-Villamizar et al. (2022), Kahalimoghadam et al. (2024), and Xiao et al. (2024). Muñoz-Villamizar et al. (2022) approach tackles a multi-period strategy for pooling different shipments to evaluate their environmental impact. The pooling strategy of vehicles provides savings of 57% in total distance, 61% in total costs, and 56% in fuel consumption. Kahalimoghadam et al. (2024) address a collaborative multi-depot green vehicle routing problem to reduce CO_2 emissions by consolidated vehicle trips. The outcome of the study demonstrates that collaborative distribution provides a substantial reduction in travel distance (43.03%) and emission (25.93%), respectively. Xiao et al. (2024) focus on developing a green vehicle routing problem where cooperation between trucks and drones for rural last-mile delivery. According to the results, the cooperative delivery of parcels provides considerable energy savings of 31.34% in total.

Table 1. **A brief overview of the literature on e-commerce logistics**

Author(s)	*Problem**	*Model***	*Solution Method****	*Objective*	*Sustainability Concern*	*Flow†*	*Postponement*
Li et al. (2013)	LIRP	ILP	HGSAA	Min	-	F, R	-
Ge et al. (2018)	2E-VRP	NLIP	TS	Min	-	F	-
Heshmati et al. (2019)	GVRP	MILP	Heuristics	Min	Energy consumption	F	-
Moons et al. (2019)	I-OP-VRP	MILP	RRT	Min	-	F	-
Liu (2020)	PDP	ILP	ACO	Max	-	F	-
Li et al. (2021)	LRP	MO-IP	LSNS-HAGA	Min, Max	-	F, R	-
Zhang et al. (2021)	MVRPSPDTW	MILP	DE	Min	-	F, R	-
Fonseca-Galindo et al. (2022)	DVRP	-	Heuristic	Min	-	F	-
Muñoz-Villamizar et al. (2022)	GVRP	MILP	-	Min	Emission	F	-
Tao et al. (2022)	MD-CVRP-OSA	IP	VNS	Min	-	F	-
Wang et al. (2022)	LRP-PS	MILP	B&P	Min	Energy consumption	F	-
Wehbi et al. (2022)	VRP-P	MILP	Clarke and Wright heuristic	Min	Emission	F	-
Tiwari and Sharma (2023)	GVRP	MILP	TS	Min	Emission	F	-
Zuhanda et al. (2023)	2E-MDCVRP	MILP	RNN	Min	-	F	-
Kahalimoghadam et al. (2024)	CMDGVRP	MOP	SAIWDSA	Min	Emission	F	-
Xiao et al. (2024)	GVRPD-SR	MILP	IALNS	Min	Energy consumption	F	-
Yu et al. (2024)	GRVP	MILP	DMPA	Min, Max	Emission	F	-
This study	GVRP	MILP	Exact – Clustering Algorithm	Min	Emission	F, R	✓

* 2E-MDCVRP: Multi-depot, capacity, two-echelon vehicle routing problem, 2E-VRP: Two echelon vehicle routing problem, CMDGVRP: Collaborative multi-depot green vehicle routing problem, DVRP: Dynamic vehicle routing problem, GVRP: Green vehicle routing problem, I-OP-VRP: Integrated order picking-vehicle routing problem, LRP: Location routing problem, LRP-PS: Location-routing problem with pick-up stations, LIRP: Location-inventory-routing problem, MD-CVRP-OSA: Multi-depot capacitated vehicle routing problem with order split and allocation, MOP: Multi-objective programming, MVRPSPDTW: Vehicle routing problem with simultaneous pickup and delivery with time windows from multiple depots, PDP: Pickup and delivery problem, VRP-P: Vehicle routing problem with portering

** ILP: Integer linear programming, IP: Integer programming, LSNS-HAGA: Large-Scale neighborhood search strategy and hybrid adaptive genetic algorithm, MILP: Mix integer linear programming, MO-IP: Multi-objective integer programming, NILP: Non-linear integer programming.

*** ACO: Ant colony optimization, B&P: Branch-and-price algorithm DE: Differential evolutionary algorithm, DMPA: Discrete marine predators algorithm, HGSAA: Hybrid genetic simulated annealing, IALNS: Improved adaptive large neighborhood search, RNN: Repetitive nearest neighbor algorithm, RRT: Record-to-record travel algorithm, SAIWDSA: Self-adaptive intelligent water drops simulated annealing, TS: Tabu search algorithm, VNS: Variable neighborhood search.

† F: Forward, R: Reverse

The review of the literature reveals that, to the best of our knowledge, no study has considered allowance in the collection stage of returned products. Therefore, this study represents a contribution to the existing literature on the subject by considering: *i)* emission to determine effects on the vehicle routing problem, *ii)* the postponement of the collection of returned items due to the limited delivery time, *iii)* proposing the cluster-based solution approach to tackle with larger-sized problems.

3. METHODOLOGY

3.1. Problem Description

The current section exhibits a formal description of the considered problem. Here, $N = \left\{D, R_{cur}, R_{pr}, \{0\}\right\}$ is the set of all nodes, where $D = \{1,2,\dots,m\}$ is a set of customers, $R_{cur} = \{1,2,\dots,n\}$ is a set of return points of the current period, $R_{pr} = \{1,2,\dots,p\}$ is a set of return points of the previous period and $\{0\}$ refers to the depot that serves as both the initial and final point of departure for vehicles. The vehicle set is represented by $K = \{1,2, \dots, k\}$.

A company is primarily responsible for forward distribution to meet customer demands. Furthermore, vehicles may collect returned items from customers due to several reasons (e.g., misdelivery, right of withdrawal, etc.) while distributing process of new items. However, the vehicle fleet may not collect all returned items because of the limited time available for the distribution process. Unsatisfied demands for the collection of returned items should be met in the next period and a penalty cost (c_p) is incurred to alleviate the negative effect of the late collection process.

The fleet consists of conventional type vehicles which produce a considerable amount of greenhouse gases to the environment. Each vehicle *k* consumes the amount of fuel in liters. To calculate the fuel consumption of each vehicle *k*, we follow Barth et al. (2005) approach. Several studies (e.g. Demir et al., 2014; Soysal et al. 2021) use this approach for fuel estimation. The energy consumption of a vehicle for traveling a distance *d* (m) at a constant speed *v* (m/s) is calculated with the help of the following formulations:

$$FC = \lambda(\eta\ (d\ /\ v) + \gamma\beta v^2 + \gamma\theta(\mu + F)d) \tag{1}$$

where FC refers to the fuel consumption, $\lambda = \xi/\kappa\psi$, $\eta = k_e N_e V_e$, $\gamma = 1/(1000\varepsilon\varpi$, $\beta = 0.5C_d A_e \rho$, and $\theta = g\sin\phi + g\ C_r \cos\phi$ (Note that we employ the notations from Barth et al., 2005 approach).

Each vehicle begins and ends its delivery operations at the depot with a fixed cost c_{fix} of operating the vehicle. Let c_{fuel} refers to the energy cost. The considered problem is to determine optimal vehicle routes by minimizing the total cost, including transport, penalty, and fixed costs.

3.2. Mathematical Model

The current section describes a MILP formulation of the addressed problem. The formulation starts with the objective function. Table 2 presents the notations considered in the model.

Table 2. Notations

Sets	*Description*
N	The set of all nodes
D	The set of forward demand
R_{cur}	The set of returned items demand in the current period
R_{pr}	The set of returned items demand in the previous period
K	The set of vehicles
Parameters	
$d_{i,j}$	the distance between nodes *i* and *j*, $i,j \in V$
$v_{i,j}$	the speed between nodes *i* and *j*, $i,j \in V$
$t_{i,j}$	the travel time between nodes *i* and *j*, $i,j \in V$
α_i	Service time at the node *i*
c_{fuel}	The fuel cost of a vehicle
c_p	A penalty cost for a delay
c_{fix}	Fixed cost of operating a vehicle
T	The latest time of the delivery
M	A sufficiently large number
$\lambda, \gamma, \beta, \eta, \theta, \mu$	Technical parameters
Variables	
$X_{i,j,k}$	1 if vehicle *k* travels from *i* to *j*, otherwise 0, $i,j \in V$
Y_i	Auxiliary variables

Minimize

$$\sum_i^N \sum_{j;i\neq j}^{N\backslash 0} \sum_k^V \lambda\left(\eta\ \left({d_{ij}}/{v_{ij}}\right) + \gamma\beta v^2 X_{i,j,k} + \gamma\theta\left(\mu X_{i,j,k}\right)d_{ij}\right)c_{fuel} + \sum_j^{R_{cur}} c_p\left(1 - \sum_{i;i\neq j}^{N}\sum_k^V X_{i,j,k}\right) + \sum_j^{N\backslash 0}\sum_k^V X_{0,j,k} \tag{2}$$

The objective function (Equation 2) comprises the cost of energy consumed due to delivery operations, penalty cost for unmet demand of returned items, and fixed cost for operating a vehicle.

Subject to:

$$\sum_j^{N\backslash 0} X_{0,j,k} = 1, \quad \forall\ k \in V \tag{3}$$

$$\sum_{i}^{N\backslash 0} X_{i,0,k} = 1, \quad \forall\, k \in V \tag{4}$$

$$\sum_{i:i\neq j}^{N} X_{i,j,k} = \sum_{i:i\neq j}^{N} X_{j,i,k}, \quad \forall\, j \in N\backslash 0,\ k \in V \tag{5}$$

$$\sum_{i:i\neq j}^{N} \sum_{k}^{V} X_{i,j,k} = 1, \quad \forall\, j \in D \tag{6}$$

$$\sum_{i:i\neq j}^{N} \sum_{k}^{V} X_{i,j,k} = 1, \quad \forall\, j \in R_{pr} \tag{7}$$

$$\sum_{i:i\neq j}^{N} \sum_{k}^{V} X_{i,j,k} \leq 1, \quad \forall\, j \in R_{cur} \tag{8}$$

$$\sum_{j:i\neq j}^{N} X_{i,j,k} \leq 1, \quad \forall\, i \in N, k \in V \tag{9}$$

$$0 \leq \sum_{i}^{N} \sum_{j:i\neq j}^{N\backslash 0} \sum_{k}^{V} t_{ij} X_{i,j,k} \leq T \tag{10}$$

$$Y_i + \sum_{k}^{V} t_{i0}\, X_{i,0,k} \leq T, \forall\, i \in N\backslash 0 \tag{11}$$

$$Y_j - Y_i - t_{ij} - \alpha_i \geq M\left(1 - \sum_{k}^{V} X_{i,j,k}\right), \forall\, i \in N, j \in N\backslash 0 \tag{12}$$

$$X_{i,j,k} \in \{0,1\}, \forall\, i,j \in N, k \in V \tag{13}$$

$$Y_i \geq 0, \forall\, i \in N \tag{14}$$

Equations 3 and 4 guarantee that a vehicle should start and end its routes at the depot {0}. Equation 5 guarantees a balance between the inflows and outflows at each of the nodes. Equations 6 and 7 guarantee that demands of forward flow points and returned items of the previous period should be met within the current period. Equation 8 allows that demand for returned items may or may not be met in the current period. Equation 9 ensures that only one vehicle can traverse from a node at the same time. Equations 10 and 11 force that the trip of a vehicle cannot exceed the latest time of the working hours. Equation 12 ensures that a vehicle can complete the tour without the possibility of undertaking any sub-tours. Equations 13 and 14 impose limitations on the decision variables.

4. CLUSTERING-BASED SOLUTION APPROACH

The clustering approach in routing problems typically involves partitioning the points to be visited into clusters based on specific characteristics, and then determining routes for each cluster individually before combining them (Erdogan and Miller-Hooks, 2012; Sutrisno and Yang, 2023). This partitioning reduces the problem size and helps shorten computation time. The suggested solution approach, which focuses on solving large-sized problem instances by breaking them down into smaller components, can be summarized in Algorithm 1.

The clustering process begins with the selection of an initial point for each cluster. To ensure that the clusters are relatively distinct from one another, it is recommended to choose the points that are farthest apart as the initial points for the clusters. Following the selection of the initial points, traveling salesman routes are created starting from these points to form the clusters. In each iteration, each potential point is analyzed for each cluster to determine which two nodes in the current route the point should be inserted between, to minimize the total distance increase. In the clustering phase of customer points, it is recommended to impose a capacity constraint on the clusters. This constraint ensures the formation of relatively balanced clusters, allowing the model to be applied effectively. If a large problem is divided into sub-problems, some sub-problems may become very small, while others remain disproportionately large. This imbalance would negate the advantages of the clustering approach.

Step 1: Initialization
  Define all parameters and set the initial values of the variables to "0".
Step 2: Determining Initial Points
  For each $k \in V$:
  For each $i \in N$:
    If i is the farthest point from the previously selected initial points, store its information.
      Add the stored point as the starting point for the k set.
Step 3: Cluster Customer points
Condition: Repeat until "*all customer points are assigned*":
  For each $j \in N\backslash 0$:
    If j has not been assigned to any set:
      In each cluster where the capacity has not been reached, calculate which two points in the cluster route, when j is added, will result in the least increase in the route length.
    If the additional distance caused by adding j to any cluster is the smallest so far, store the information about the cluster and the two points between which it will be added.
  Add the stored point between the two determined points in the relevant set.
  Assign a vehicle to this cluster.

Figure 1. Clustering-based solution approach

5. FINDINGS

The present section describes a numerical analysis to demonstrate the suitability of the model for addressing the aforementioned problem. We obtained the results by using the CPLEX 12.6 optimization package on a computer with a Pentium(R) i5 2.40GHz CPU and 16GB memory.

First, we outline the problems and the data utilized for analysis. Next, we evaluate optimal solutions across various scenarios. We provide Key Performance Indicators (KPIs): *(i)* total cost, *(ii)* total fuel amount, *(iii)* total postponement number, *(iv)* total traveled distance, *(v)* total traveled time, and (vi) total emission amount.

5.1. Base Case

We use the data from the Pollution Routing Problem Instance Library (2024). Then, we have adapted the distances of the UK50_01 instance by considering one-fourth of the original distances to imitate an urban environment. The logistics network involves a depot and 25 customers for forward and 25 customers for reverse flow points.

For the base case, the vehicle fleet consists of two homogeneous vehicles with a 2000 TL fixed cost. The fuel cost is approximately 45 TL per liter. The penalty cost for unsatisfied demands for the collection of returned items is 500 TL per customer. Vehicles should complete both forward and reverse transportation within 8 hours. Table 3 presents base case results considering the defined KPIs.

Table 3. Base case results

KPIs	*Value*
Total cost (TL)	11390
Total fuel amount (liter)	43.22
Total postponement number (customer)	7
Total traveled distance (km)	446.95
Total traveled time (hour)	7.75
Total emission amount (kg)	227.41

According to the result, vehicles were not able to visit 7 customers with demand for return items within working hours. Thus, the company should pay 3500 TL to unsatisfied customers to alleviate the negative effects of postponed delivery. To complete the delivery, vehicles consume approximately 43 liters by releasing 227 kg of CO_2 into the air.

5.2. The Effect of Return Postponement

The proposed model respects the postponement of returned items due to the limited delivery time. This subsection aims to show the effect of return postponement on KPIs through an additional analysis. We assume that both forward and reverse demands should be met on the same day, so reverse demand cannot be postponed. This means that equation 10 can be violated by the extended total travel time of vehicles. Equation 8 has been replaced with Equation 15.

$$\sum_{i:i\neq j}^{N} \sum_{k}^{V} X_{i,j,k} = 1, \quad \forall\, j \in R_{cur} \qquad (15)$$

Table 4. Summary results for respecting the postponement of returned items

KPIs	*Value*
Total cost (TL)	8967
Total fuel amount (liter)	55.18
Total postponement number (customer)	0
Total traveled distance (km)	570.61
Total traveled time (hour)	9.9
Total emission amount (kg)	290.33

The results of both total fuel consumption and total emission amount have been increased by approximately 27% (Table 4), due to longer vehicle trips than the base case. Although total cost decreased because of no reverse demand postponement, vehicles did not visit all customers within the pre-determined delivery time. This solution becomes unfeasible for the considered problem. It seems more realistic to consider the postponement of reverse demand rather than forward demand for decision-makers in real-life applications. Since in real life, the distribution process has to be carried out within limited times of the day, decision-makers have to take the risk of postponing some returns.

5.3. The Effect of the Return Collection

This subsection demonstrates the effect of return collection on KPIs, we assume that forward and reverse demands have been collected by different vehicles. Thus, routes of forward and reverse demands have been separated from each other. We replaced Equations 6-8 with Equations 16-18.

$$\sum_{i:i\neq j}^{N} X_{i,j,1} = 1, \quad \forall\, j \in D \tag{16}$$

$$\sum_{i:i\neq j}^{N} X_{i,j,2} = 1, \quad \forall\, j \in R_{pr} \tag{17}$$

$$\sum_{i:i\neq j}^{N} X_{i,j,2} \leq 1, \quad \forall\, j \in R_{cur} \tag{18}$$

Table 5. Summary results for the effect of return collection on KPIs

KPIs	*Value*
Total cost (TL)	11087
Total fuel amount (liter)	78.75
Total postponement number (customer)	0
Total traveled distance (km)	814.14
Total traveled time (hour)*	7.42
Total traveled time (hour)**	6.70
Total emission amount (kg)	414.23

* Vehicle responsible for forward distribution
** Vehicle responsible for reverse collection

Table 5 presents the KPIs of the network where routes of forward and reverse demands are separately delivered by different vehicles. The results demonstrate that both the total fuel amount and total emission amount have considerably increased (i.e., approximately 82%) for the base case. The main reason is the inefficient routing of vehicles although the total postponement number is none. These results imply that separating distribution and collection operations is not an efficient decision for a company concerning total fuel consumption and total emissions released into the air because of the long routes of vehicles.

5.4. The Effect of Considering Emission

In the proposed model, total transportation energy consumption or emissions serve as indicators to evaluate the performance of logistics operations in terms of environmental externalities. The model quantifies the overall environmental impact in terms of cost, incorporating fuel and electricity consumption components within the objective function. In this subsection, the objective function is adjusted to enable the model to deliver an optimal solution that minimizes the total environmental impact. In specific, penalty cost for unmet demand of returned items and fixed cost for operating a vehicle are removed from the objective function. The new formulation is optimized with an environmental objective function that focuses solely on the emission levels generated by fossil fuel-powered vehicles. Table 7 presents where the objective function is the same as the base case and the objective is the minimization of emissions, respectively.

Table 7. Resulting vehicle routes from the distribution networks where the objective function is the same as the base case and the objective is the minimization of emissions, respectively

Vehicle	*Route*
Base Case	
1	Depot-1-2-4-6-7-8-13-14-15-16-17-21-25-26-37-38-41-44-45-46-47-48-50-Depot
2	Depot-3-5-9-10-11-12-18-19-20-22-23-24-27-29-30-33-34-42-43-49-Depot
The adjusted model for minimizing emission	
1	Depot-1-2-4-6-7-8-13-14-15-16-17-21-25-45-49-Depot
2	Depot-3-5-9-10-11-12-18-19-20-22-23-24-46-47-48-50-Depot

The results indicate that the solution from the adjusted model achieves a reduction of nearly 17% in total emission amount. However, adopting environmentally friendly measures leads to postponing all customers who expect the collection of returns in the current period. The postponement of returns may cause a significant number of unsatisfied customers. Furthermore, the adjusted model generates different vehicle routes compared to those observed in the base cases. The analyses presented in this subsection show that environmentally friendly delivery plans may not be economically viable for transportation companies in last-mile logistics. To mitigate the negative environmental externalities of transportation operations, vehicle routes, and fleet composition may need to be adjusted.

5.5. Numerical Analyses on Larger-Sized Problems

In this subsection, we investigate the performance of the clustering-based solution approach in relatively larger instances. The data for the large-sized problems are also taken from “The Pollution-Routing Problem Instance Library". We have used 5 instances from each problem set with 150 customers (UK150_01 to `UK150_05), and 200 customers (UK200_01 to `UK200_05). In line with the base case, the distances of instances that include 150 and 200 customers by considering one-six and one-eighth of the original distances to emulate urban logistics network for last-mile delivery.

Table 8. Comparison of the performance exact solutions and the clustering-based solution algorithm in large-sized instances

		Total cost (TL)			*Solution Time (hours)*		
No	*Instance*	*Exact solution*	*The Proposed Approach*	*% diff.*	*Exact Solution*	*The Proposed Approach*	*% diff.*
1	UK150_01	26497	27428	3.51	6.68	0.84	-87.37
2	UK150_02	30500	32290	5.87	6.36	0.90	-85.83
3	UK150_03	21973	23150	5.36	6.45	0.71	-88.96
4	UK150_04	23965	26054	8.72	6.87	0.73	-89.34
5	UK150_05	21000	22063	5.06	6.39	0.53	-91.71
6	UK200_01	20004	21252	6.24	12.76	1.71	-86.58
7	UK200_02	20485	22704	10.83	12.68	1.94	-84.68
8	UK200_03	20996	21995	4.75	12.92	1.98	-84.70
9	UK200_04	20551	21516	4.69	12.98	1.88	-85.48
10	UK200_05	24500	25489	4.04	12.95	1.57	-87.87

The results show that the clustering-based solution approach provides promising solutions concerning total cost. Except for Instance 7 (UK200_02), the total cost difference between the exact solution and the solutions obtained from the proposed algorithm does not exceed 10%. This shows that the algorithm is an effective tool for managers to employ feasible delivery plans in last-mile delivery operations. Furthermore, the clustering-based solution approach outperforms the MILP model in terms of solution time, with the algorithm being, on average, 87% faster than the MILP model. Therefore, the proposed solution approach can be considered a robust alternative for decision-makers when handling practically-sized routing instances.

6. CONCLUSION

The extensive adoption of the Internet and technological advancements provide a significant contribution to the growth of the e-commerce industry, supplanting traditional trade methods. Especially in extraordinary outbreaks such as the COVID-19 era, e-commerce has been considered a more important and preferred method for consumers. Customers' demand for fast and reliable delivery from the e-commerce industry requires timely and error-free distribution of products to customers. Last-mile logistics, which primarily involves transporting products from local distribution centers to customers within a short time frame, is the crucial stage in the e-commerce supply chain. Every improvement in logistics leads to time and cost savings for logistics companies and the entire economy through the supply chain (Şahinaslan et al., 2023).

This study addresses a vehicle routing problem under returns and emission consideration in B2C e-commerce logistics. The proposed MILP model is unique for the considered problem in respecting comprehensive emissions function and simultaneous delivery of both forward and reverse demands. We presented the added value of the MILP model with a base case and two additional analyses. The numerical analysis for the base case shows that the suggested model can assist decision-makers in coordinating forward distribution and reverse collection decisions within the context of sustainable e-commerce logistics. The results of additional analyses have indicated that it would be beneficial to consider the possibility of simultaneous return collection and the postponement of returns. The result of the adjusted model for minimizing emission shows that a reduction of nearly 17% in total emission amount can be achieved, however, the adjusted model postpones all demand for the collection of returned items. Furthermore, the cluster-based solution approach causes a considerable decrease in solution time while providing promising solutions. Disregarding these aspects may lead companies to endure increased fuel and emissions in the e-commerce industry. The current study reduces emissions by improving routes. Future research can consider electric vehicles, hydrogen-fuel-cell vehicles, or even drones (McKinsey & Company, 2021: 3).

It is important to acknowledge the limitations of the research to inform future attempts. Firstly, it should be noted that this study does not take into account the potential uncertainty regarding forward and reverse demands. Secondly, the vehicle capacity and weights of the products in question are disregarded, despite the potential for such factors to influence the optimal routing of a vehicle. In this study, only static demand has been taken into consideration, however, demands can be changed dynamically due to various reasons.

A future attempt could be to address pickup points instead of delivering and collecting parcels directly to and from customer locations in both forward and reverse flows. Another possible extension of the paper is to consolidate deliveries to reduce the number of vehicles used. These dimensions offer opportunities for future studies on the topic.

Conflict of Interest
No potential conflict of interest was declared by the author.

Funding
Any specific grant has not been received from funding agencies in the public, commercial, or not-for-profit sectors.

Compliance with Ethical Standards
It was declared by the author that the tools and methods used in the study do not require the permission of the Ethics Committee.

Ethical Statement
It was declared by the author that scientific and ethical principles have been followed in this study and all the sources used have been properly cited.

REFERENCES

Al Mashalah, H., Hassini, E., Gunasekaran, A. and Bhatt, D. (2022). "The Impact of Digital Transformation on Supply Chains through E-Commerce: Literature Review and A Conceptual Framework", *Transportation Research Part E: Logistics and Transportation Review*, 165, 102837.

Apaydin, O. Gonullu, M.T. (2008). "Emission Control with Route Optimization in Solid Waste Collection Process: A Case Study", *Sadhana*, 33, 71-82.

Barth, M., Younglove, T. and Scora, G. (2005). "Development of A Heavy-Duty Diesel Modal Emissions and Fuel Consumption Model", Technical Report, California Path Program Institute of Transportation Studies, University of California.

Bektaş, T. and Laporte, G. (2011). "The Pollution-Routing Problem", *Transportation Research Part B: Methodological*, 45(8), 1232-1250.

Çimen, M. and Soysal, M. (2017). "Time-Dependent Green Vehicle Routing Problem with Stochastic Vehicle Speeds: An Approximate Dynamic Programming Algorithm", *Transportation Research Part D: Transport and Environment*, 54, 82-98.

Dantzig, G.B. and Ramser, J.H. (1959). "The Truck Dispatching Problem", *Management Science*, 6(1), 80-91.

Delfmann, W., Albers, S. and Gehring, M. (2002). "The Impact of Electronic Commerce on Logistics Service Providers", *International Journal of Physical Distribution and Logistics Management*, 32(3), 203-222.

Demir, E., Bektaş, T. and Laporte, G. (2014). "The Bi-Objective Pollution-Routing Problem", *European Journal of Operational Research*, 232(3), 464-478.

Dündar, H., Ömürgönülşen, M. and Soysal, M. (2021). "A Review on Sustainable Urban Vehicle Routing", *Journal of Cleaner Production*, 285, 125444.

Erdoğan, S. and Miller-Hooks, E. (2012). "A Green Vehicle Routing Problem", *Transportation Research Part E: Logistics and Transportation Review*, 48(1), 100-114.

EuroCommerce. (2024). "European E-Commerce Report 2023", https://ecommerce-europe.eu/wp-content/uploads/2023/11/European-Ecommerce-Report-2023-Light-Version.pdf, (Accessed:17.06.2024)

Fonseca-Galindo, J. C., de Castro Surita, G., Neto, J. M., de Castro, C. L. and Lemos, A.P. (2022). "A Multi-Agent System for Solving the Dynamic Capacitated Vehicle Routing Problem with Stochastic Customers Using Trajectory Data Mining", *Expert Systems with Applications*, 195, 116602.

Ge, X., Xue, G. and Wen, P. (2018). "Proactive Two-Level Dynamic Distribution Routing Optimization Based on Historical Data", *Mathematical Problems in Engineering*, 2018(1), 5191637.

Güngördü Belbağ, A. (2022). "Impacts of Covid-19 Pandemic on Consumer Behavior in Turkey: A Qualitative Study", *Journal of Consumer Affairs*, 56(1), 339-358.

Heshmati, S., Verstichel, J., Esprit, E. and Berghe, G.V. (2019). "Alternative E-Commerce Delivery Policies: A Case Study Concerning the Effects on Carbon Emissions", *EURO Journal on Transportation and Logistics*, 8(3), 217-248.

Kahalimoghadam, M., Thompson, R.G. and Rajabifard, A. (2024). "Self-Adaptive Metaheuristic-based Emissions Reduction in a Collaborative Routing Problem", *Sustainable Cities and Society*, 105577.

Kawasaki, T., Wakashima, H. and Shibasaki, R. (2022). "The Use of E-Commerce and the COVID-19 Outbreak: A Panel Data Analysis in Japan", *Transport Policy*, 115, 88-100.

Li, Y., Guo, H., Wang, L. and Fu, J. (2013). "A Hybrid Genetic-Simulated Annealing Algorithm for the Location-Inventory-Routing Problem Considering Returns under E-Supply Chain Environment", *The Scientific World Journal*, 2013(1), 125893.

Li, J., Zhao, Z. and Cheng, T. (2021). "Research on LRP Integration of E-Commerce Logistics under the Background of Integration of Collection and Distribution", *Discrete Dynamics in Nature and Society*, 2021(1), 6038947.

Liu, W. (2020). "Route Optimization for Last-Mile Distribution of Rural E-Commerce Logistics Based on Ant Colony Optimization", *IEEE Access*, 8, 12179-12187.

Mancini, S. (2017). "The Hybrid Vehicle Routing Problem", *Transportation Research Part C: Emerging Technologies*, 78, 1-12.

Mangiaracina, R., Marchet, G., Perotti, S. and Tumino, A. (2015). "A Review of the Environmental Implications of B2C E-Commerce: A Logistics Perspective", *International Journal of Physical Distribution & Logistics Management*, 45(6), 565-591.

Matthews, H.S., Hendrickson, C.T. and Soh, D.L. (2001). "Environmental and Economic Effects of E-Commerce: A Case Study of Book Publishing and Retail Logistics", *Transportation Research Record*, 1763(1), 6-12.

McKinnon, A., (2007). "CO2 Emissions from Freight Transport in the UK", Climate Change Working Group of the Commission for Integrated Transport, https://www.researchgate.net/publication/318710769_CO_2_Emissions_from_Freight_Transport_in_the_UK_Report_prepared_for_the_Climate_Change_Working_Group_of_the_Commission_for_Integrated_Transport_2007, (Accessed: 11.06.24).

McKinsey & Company (2021). "Efficient and Sustainable Last-Mile Logistics: Lessons from Japan", https://www.mckinsey.com/industries/travel-logistics-and-infrastructure/our-insights/efficient-and-sustainable-last-mile-logistics-lessons-from-japan, (Accessed:17.06.2024).

Meyer, H. (1999). "Many Happy Returns", *The Journal of Business Strategy*, 20(4), 27.

Moons, S., Braekers, K., Ramaekers, K., Caris, A., and Arda, Y. (2019). "The Value of Integrating Order Picking and Vehicle Routing Decisions in A B2C E-Commerce Environment", *International Journal of Production Research*, 57(20), 6405-6423.

Muñoz-Villamizar, A., Velázquez-Martínez, J.C., Mejía-Argueta, C. and Gámez-Pérez, K. (2022). "The Impact of Shipment Consolidation Strategies for Green Home Delivery: A Case Study in A Mexican Retail Company", *International Journal of Production Research*, 60(8), 2443-2460.

OliverWyman (2021). "Is E-commerce Good for Europe? Economic and Environmental Impact Study", https://www.oliverwyman.com/our-expertise/insights/2021/apr/is-e-commerce-good-for-europe.html, (Accessed:18.06.2024).

Pollution Routing Problem Instance Library. (2024). "Data Set of the Pollution-Routing Problem", https://www.researchgate.net/publication/283908373_, (Accessed: 11.06.2024).

Ranieri, L., Digiesi, S., Silvestri, B. and Roccotelli, M. (2018). "A Review of Last Mile Logistics Innovations in An Externalities Cost Reduction Vision", *Sustainability*, 10(3), 782.

Risberg A. (2023). "A Systematic Literature Review on Ecommerce Logistics: Towards An E-Commerce and Omni-Channel Decision Framework", *The International Review of Retail, Distribution and Consumer Research*, 33(1), 67-91.

Samut, P.K. (2023). "OECD Ülkelerinin Yeşil Lojistik Performansı ile Enerji, Sağlık Ekonomisi ve Çevre İlişkisinin Analizi", *Verimlilik Dergisi*, Döngüsel Ekonomi ve Sürdürülebilirlik (SI), 67-82.

Seghezzi, A. and R. Mangiaracina (2021). "Investigating Multi-Parcel Crowdsourcing Logistics for B2C e-Commerce Last-Mile Deliveries", *International Journal of Logistics Research and Applications*, 24(5), 456-472.

Silva, C., Ross, M. and Farias, T. (2009). "Evaluation of Energy Consumption, Emissions and Cost of Plug-In Hybrid Vehicles", *Energy Conversion and Management*, 50(7), 1635-1643.

Soysal, M., Çimen, M. and Belbağ, S. (2020). "Pickup and Delivery with Electric Vehicles under Stochastic Battery Depletion", *Computers & Industrial Engineering*, 146, 106512.

Soysal, M., Belbağ, S. and Sel, Ç. (2021). "A Closed Vendor Managed Inventory System under A Mixed Fleet of Electric and Conventional Vehicles", *Computers & Industrial Engineering*, 156, 107210.

Sutrisno, H., Yang, C.L., 2023. "A Two-Echelon Location Routing Problem with Mobile Satellites for Last-Mile Delivery: Mathematical Formulation and Clustering-Based Heuristic Method", *Annals of Operations Research*, 323(1-2), 203-228.

Şahinaslan, Ö., Karatas, C. and Şahinaslan, E. (2023). "Lojistik Depolarda Sipariş Toplama ve Konumlandırmaya Yönelik Yenilikçi Bir Yaklaşım", *Verimlilik Dergisi*, 57(3), 491-512.

Tao, Y., Lin, C. and Wei, L. (2022). "Metaheuristics for A Large-Scale Vehicle Routing Problem of Same-Day Delivery in E-Commerce Logistics System", *Journal of Advanced Transportation*, 2022(1), 8253175.

Tiwari, K.V. and Sharma, S.K. (2023). "An Optimization Model for Vehicle Routing Problem in Last-Mile Delivery", *Expert Systems with Applications*, 222, 119789.

T.C. Ticaret Bakanlığı. (2023). "Türkiye'de E-Ticaretin Görünümü Raporu", https://ticaret.gov.tr/data/66506fa313b87685dc0dbce8/2023%20y%C4%B1l%C4%B1%20Tu%CC%88rkiye'de%20E-Ticaretin%20Go%CC%88ru%CC%88nu%CC%88mu%CC%88%20Raporu.pdf, (Accessed:10.06.2024).

United Nations. (2024a). "17 Sustainable Development Goals", https://sdgs.un.org/goals, (Accessed:14.06.2024).

United Nations. (2024b). "The Sustainable Development Goals Report 2024", https://unstats.un.org/sdgs/report/2024/, (Accessed: 14.06.2024

United Nations. (2023). "Emissions Gap Report 2023", https://www.unep.org/resources/emissions-gap-report-2023, (Accessed: 14.06.2024).

UNCTAD. (2024). "Digital Economy Report 2023", https://unctad.org/publication/digital-economy-report-2024, (Accessed:01.07.2024).

UNStats. (2019). “Take Urgent Action to Combat Climate Change and Its Impacts”, https://unstats.un.org/sdgs/report/2019/goal-13/#:~:text=To%20limit%20global%20warming%20to,net%20zero%20emissions%20by%202050, (Accessed: 01.07.2024).

Vanelslander, T., Deketele, L. and Van Hove, D. (2013). “Commonly Used E-commerce Supply Chains for Fast Moving Consumer Goods: Comparison and Suggestions for Improvement”, *International Journal of Logistics*, 16(3), 243-256.

Viu-Roig, M. and Alvarez-Palau, E.J. (2020). “The Impact of E-Commerce-Related Last-Mile Logistics on Cities: A Systematic Literature Review”, *Sustainability*, 12(16), 6492.

Wang, M., Zhang, C., Bell, M.G. and Miao, L. (2022). “A Branch-and-Price Algorithm for Location-Routing Problems with Pick-Up Stations in the Last-Mile Distribution System”, *European Journal of Operational Research*, 303(3), 1258-1276.

Wehbi, L., Bektaş, T. and Iris, Ç. (2022). “Optimising Vehicle and On-Foot Porter Routing in Urban Logistics”, *Transportation Research Part D: Transport and Environment*, 109, 103371.

Xiao, J., Li, Y., Cao, Z. and Xiao, J. (2024). “Cooperative Trucks and Drones for Rural Last-Mile Delivery with Steep Roads”, *Computers & Industrial Engineering*, 187, 109849.

Yu, X., Li, Y., Liu, J. and Zhou, H. (2024). “Solving Low-Carbon Last Mile Delivery Problem Using Discrete Marine Predators Algorithm”, *Applied Soft Computing*, 165, 112112.

Zhang, M., Pratap, S., Zhao, Z., Prajapati, D. and Huang, G.Q. (2021). “Forward and Reverse Logistics Vehicle Routing Problems with Time Horizons in B2C E-Commerce Logistics”, *International Journal of Production Research*, 59(20), 6291-6310.

Zuhanda, M.K., Suwilo, S., Sitompul, O.S., Caraka, R.E., Kim, Y. and Noh, M. (2023). “Optimization of Vehicle Routing Problem in the Context of E-commerce Logistics Distribution”, *Engineering Letters*, 31(1).

VERİMLİLİK DERGİSİ
JOURNAL OF PRODUCTIVITY

Analysis of Logistics 4.0 Service Provider Alternatives with CRITIC-Based WASPAS Method

Muhammet Enes Akpınar[1]

ABSTRACT

Purpose: This study aims to evaluate and identify the most suitable logistics service providers within the framework of Logistics 4.0, shaped by digital transformation and Industry 4.0 technologies. Logistics 4.0 seeks to optimize logistics processes using innovative technologies such as smart systems and big data analytics. In this context, selecting the right service provider is of strategic importance for businesses. This study intends to assist companies in making accurate decisions in this complex process.

Method: The CRITIC (Criteria Importance Through Intercriteria Correlation) based WASPAS (Weighted Aggregated Sum Product Assessment) method was employed. The CRITIC method was used to determine the objective weights of the criteria, while the WASPAS method utilized these weights to calculate the overall performance scores of the alternatives.

Findings: The results of the study reveal the key criteria that businesses should consider when selecting Logistics 4.0 service providers and identifying the top-performing service providers.

Originality: This study highlights the advantages and effectiveness of using the combined CRITIC and WASPAS methods in the selection of service providers in the logistics sector. Additionally, it contributes to the literature on the selection of Logistics 4.0 service providers.

***Keywords*:** Logistics 4.0, Multi-Criteria Decision Making, CRITIC, WASPAS.

JEL Codes: C44, M10, D70.

Lojistik 4.0 Hizmet Sağlayıcı Alternatiflerinin CRITIC tabanlı WASPAS Yöntemi ile Analizi

ÖZET

Amaç: Bu çalışmanın amacı, dijital dönüşüm ve Endüstri 4.0 teknolojileriyle şekillenen Lojistik 4.0 kavramı çerçevesinde, lojistik hizmet sağlayıcılarının değerlendirilmesi ve en uygun hizmet sağlayıcının belirlenmesidir. Lojistik 4.0, akıllı sistemler ve büyük veri analitiği gibi yenilikçi teknolojileri kullanarak lojistik süreçleri optimize etmeyi hedefler. Bu bağlamda, doğru hizmet sağlayıcıyı seçmek, işletmeler için stratejik bir öneme sahiptir. Çalışma, işletmelerin bu karmaşık süreçte doğru kararlar almasına yardımcı olmayı amaçlamaktadır.

Yöntem: CRITIC (Criteria Importance Through Intercriteria Correlation) tabanlı WASPAS (Weighted Aggregated Sum Product Assessment) yöntemi kullanılmıştır. CRITIC yöntemi ile kriterlerin objektif ağırlıkları belirlenmiş, WASPAS yöntemi ise bu ağırlıkları kullanarak alternatiflerin genel performans skorlarını hesaplamıştır.

Bulgular: Çalışma sonuçları, işletmelerin Lojistik 4.0 hizmet sağlayıcılarını seçerken dikkat etmeleri gereken önemli kriterleri ve en iyi performans gösteren hizmet sağlayıcıları ortaya koymuştur.

Özgünlük: Bu çalışma, CRITIC ve WASPAS yöntemlerinin birlikte kullanımının, lojistik sektöründe hizmet sağlayıcı seçiminde sağladığı avantajları ve yöntemlerin etkinliğini vurgulamaktadır. Ayrıca, lojistik sektöründe Lojistik 4.0 hizmet sağlayıcılarının seçimi konusunda literatüre katkı sağlamaktadır.

Anahtar Kelimeler: Lojistik 4.0, Çok Kriterli Karar Verme, CRITIC, WASPAS.

JEL Kodları: C44, M10, D70.

[1] İzmir Bakırçay University, Faculty of Economics and Administrative Sciences, İzmir, Türkiye

Corresponding Author: Muhammet Enes Akpınar, enes.akpinar@bakircay.edu.tr

DOI: 10.51551/verimlilik.1523739
Research Article | Submitted: 28.07.2024 | Accepted: 29.09.2024
Cite: Akpınar, M.E. (2025). “Analysis of Logistics 4.0 Service Provider Alternatives with CRITIC-Based WASPAS Method”, *Verimlilik Dergisi,* Productivity for Logistics (SI), 77-88.

1. INTRODUCTION

The logistics sector is undergoing a significant transformation driven by digitalization and the integration of Industry 4.0 technologies. This new paradigm has given rise to the concept of Logistics 4.0, which aims to make logistics processes more efficient, flexible, and sustainable. Logistics 4.0 involves the integration of innovative technologies such as smart systems, big data analytics, the Internet of Things (IoT), artificial intelligence, and automation technologies (Wang et al., 2020; Hofmann & Rüsch, 2017). The adoption of these technologies not only optimizes traditional logistics operations but also creates new opportunities for enhancing the entire supply chain. Consequently, the selection of suitable logistics service providers becomes a critical strategic decision for businesses seeking to leverage the full potential of Logistics 4.0.

The criteria for evaluating logistics service providers in the context of Logistics 4.0 are diverse and multifaceted. Key criteria include cost, service quality, technology utilization, flexibility, and sustainability. Each of these criteria plays a crucial role in determining the overall effectiveness and competitiveness of a logistics service provider (Govindan et al., 2018; Büyüközkan & Göçer, 2018). For instance, the cost criterion evaluates the financial implications of choosing a particular provider, while service quality assesses the reliability and performance of logistics services. Technology utilization examines the extent to which providers integrate advanced technologies into their operations, and flexibility measures their ability to adapt to changing conditions. Finally, sustainability considers the environmental and social impacts of logistics activities (Kannan et al., 2020).

In this context, Multi-Criteria Decision Making (MCDM) methods have emerged as valuable tools for evaluating and selecting logistics service providers. Among these methods, the CRITIC (Criteria Importance Through Intercriteria Correlation) and WASPAS (Weighted Aggregated Sum Product Assessment) techniques have gained prominence due to their robust analytical capabilities. The Criteria Importance Through Intercriteria Correlation (CRITIC) method helps in determining the objective weights of various criteria, while the Weighted Aggregated Sum Product Assessment (WASPAS) method utilizes these weights to calculate the overall performance scores of alternatives (Zavadskas et al., 2012; Yazdani et al., 2019). By combining these methods, decision-makers can achieve a more comprehensive and accurate assessment of logistics service providers. This integrated approach addresses the complexity and multi-dimensionality of the decision-making process in the Logistics 4.0 environment. One of the central aims of Logistics 4.0 is to optimize operational efficiency through the use of smart technologies, data-driven decision-making, and automation. In this context, the selection of service providers that can deliver efficient logistics solutions is critical for businesses seeking competitive advantage. This study not only identifies the best-performing service providers but also focuses on how these providers contribute to improved efficiency in logistics operations.

This study aims to contribute to the decision-making process for selecting Logistics 4.0 service providers by offering a systematic approach for identifying the most efficient providers. A review of the existing literature reveals a lack of objective and systematic MCDM methods specifically tailored to Logistics 4.0 service provider selection. This study fills that gap by integrating the CRITIC and WASPAS methods, providing a comprehensive and objective evaluation framework. The original contribution of this research lies in its proposal of a hybrid approach that addresses the complexity of decision-making in Logistics 4.0.

The rest of the study is organized as follows. In the second section, the concept of Logistics 4.0 is explained in detail. In the third section, the methods used in the study are presented. In the fourth section, the application area of the study is given. In the last section, the results obtained in the study are interpreted.

LOGISTICS 4.0

Industry 4.0 represents the digital transformation of manufacturing processes, encompassing automation, data exchange, smart systems, and the integration of advanced manufacturing techniques. This paradigm shift has brought about revolutionary changes across a wide range of areas, from production lines to supply chains. Key technologies driving Industry 4.0 include the IoT, cyber-physical systems, big data analytics, and Artificial Intelligence (AI). These technologies enable real-time monitoring, predictive maintenance, and enhanced decision-making capabilities, significantly improving operational efficiency and flexibility (Hofmann & Rüsch, 2017; Wang et al., 2020). As a result, companies adopting Industry 4.0 principles can achieve higher levels of productivity and competitiveness in the global market.

Logistics 4.0, a subset of Industry 4.0, specifically focuses on the logistics and supply chain sectors. It aims to optimize logistics processes using advanced technologies and digital innovations. Logistics 4.0 leverages IoT to connect various components of the supply chain, enabling real-time tracking and monitoring of goods and assets. This connectivity enhances transparency, reduces delays, and improves overall supply chain efficiency (Barreto et al., 2017). Moreover, big data analytics plays a crucial role in Logistics 4.0 by providing insights into patterns and trends, helping companies make data-driven decisions and anticipate potential disruptions. By integrating these technologies, Logistics 4.0 seeks to create a more responsive and agile supply chain.

One of the fundamental aspects of Logistics 4.0 is the use of autonomous vehicles and drones for transportation and delivery. Autonomous trucks and drones equipped with advanced sensors and navigation systems can operate with minimal human intervention, reducing labor costs and increasing delivery speed and accuracy. These autonomous systems can optimize delivery routes in real time, avoiding traffic congestion and minimizing fuel consumption. Additionally, warehouses are becoming increasingly automated with the use of robotic systems for sorting, picking, and packing goods (Saarikko et al., 2020; Fottler et al., 2020: 38). This automation not only enhances efficiency but also reduces the risk of human error, ensuring a more reliable logistics operation.

The integration of AI and machine learning in Logistics 4.0 further enhances decision-making and operational efficiency. AI algorithms can analyze vast amounts of data from various sources, such as weather conditions, traffic patterns, and inventory levels, to optimize logistics processes. For instance, predictive analytics can forecast demand and adjust inventory levels accordingly, reducing the risk of stockouts or overstocking. Machine learning models can also identify patterns in transportation data to improve route planning and delivery schedules (Ivanov et al., 2019; Choi et al., 2019). By utilizing these advanced technologies, companies can achieve greater operational efficiency, cost savings, and improved customer satisfaction.

Sustainability is another critical aspect of Logistics 4.0. The integration of green technologies and practices aims to reduce the environmental impact of logistics operations. Electric and hybrid vehicles, for instance, are being adopted to lower carbon emissions. Additionally, smart logistics systems can optimize energy consumption in warehouses and transportation networks. The use of recyclable and biodegradable packaging materials is also being promoted to minimize waste (de Oliveira and Handfield, 2019; Agyabeng-Mensah et al., 2020). By focusing on sustainability, Logistics 4.0 not only addresses environmental concerns but also enhances the corporate social responsibility of businesses.

Logistics 4.0 represents a significant evolution in the logistics and supply chain sectors, driven by the integration of advanced digital technologies. By leveraging IoT, AI, autonomous systems, and sustainable practices, Logistics 4.0 aims to create more efficient, agile, and environmentally friendly logistics operations. This transformation offers numerous benefits, including cost savings, improved customer satisfaction, and a reduced environmental footprint. As businesses continue to adopt and integrate these technologies, the logistics industry is poised for a future of increased innovation and competitiveness (Wang et al., 2020; Hofmann and Rüsch, 2017).

3. CRITIC and WASPAS METHODS

3.1 CRITIC Method

The CRITIC method is an MCDM technique used to determine the objective weights of evaluation criteria. Developed by Diakoulaki et al. (1995), the CRITIC method is particularly useful in scenarios where subjective judgments might introduce biases, as it relies on the intrinsic properties of the data to assign weights to criteria. This method considers both the contrast intensity of each criterion and the conflict or correlation between criteria, thus providing a comprehensive approach to weight determination. The CRITIC method involves several steps:

1. Normalization: The first step in the CRITIC method is to normalize the decision matrix. This is done to bring all the criteria to a comparable scale. The normalized value r_{ij} of each element is calculated using Equation 1.

$$r_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \tag{1}$$

2. Standard Deviation Calculation: The standard deviation σ_j of each criterion is then calculated using Equation 2. This measures the contrast intensity or the degree of differentiation of each criterion.

$$\sigma_j = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(r_{ij} - \bar{r}_j)^2} \tag{2}$$

3. Correlation Coefficient Calculation: The correlation coefficient ρ_{jk} between criteria j and k is calculated via Equation 3 to assess the degree of conflict between criteria.

$$\rho_{jk} = \frac{\sum_{i=1}^{n}(r_{ij} - \bar{r}_j)(r_{ik} - \bar{r}_k)}{\sqrt{\sum_{i=1}^{n}(r_{ij} - \bar{r}_j)^2 (r_{ik} - \bar{r}_k)^2}} \tag{3}$$

4. Information Content Calculation: The amount of information provided by each criterion C_j is then determined (Equation 4). This considers both the standard deviation and the correlation with other criteria.

$$C_j = \sigma_j \sqrt{\sum_{k=1}^{m}(1 - p_{jk})} \quad (4)$$

5. Weight Calculation: Finally, the weight W_j of each criterion is calculated by normalizing the information content values (Equation 5).

$$W_j = \frac{C_j}{\sum_{j=1}^{m} C_j} \quad (5)$$

The CRITIC method is particularly advantageous because it provides an objective way to determine the weights of criteria, eliminating potential biases associated with subjective weight assignment. It considers both the variability of criteria and their interrelationships, ensuring that the final weights reflect the true importance of each criterion in the decision-making process (Diakoulaki et al., 1995; Zavadskas et al., 2012).

By integrating the CRITIC method with other MCDM techniques, such as the WASPAS, decision-makers can achieve more accurate and reliable evaluations of alternatives. This integrated approach leverages the strengths of both methods, providing a robust framework for complex decision-making scenarios in various fields, including logistics, supply chain management, and beyond (Yazdani et al., 2019; Zavadskas et al., 2012).

The CRITIC method has been widely applied in MCDM problems across various domains. Ahmad et al. (2023) integrated the CRITIC method with the MABAC method for identifying occupational hazards using q-rung picture fuzzy sets. Taletović (2023) reviewed the application of MCDM methods in warehouse management, highlighting the effectiveness of the CRITIC method. Lai and Liao (2021) employed the CRITIC method in the DNMA approach to evaluate blockchain platforms, emphasizing the method's ability to reflect criteria correlations. Zhang et al. (2023) introduced the Cloud-CRITIC-PDR method, combining the CRITIC method with a cloud model and probabilistic dominance relations for hybrid MCDM. Abouhawwash and Jameel (2023) applied the CRITIC method to evaluate solar power installations under a Neutrosophic MCDM model.

Nabavi et al. (2024) assessed the sensitivity of MCDM methods, including CRITIC, in chemical engineering optimization applications. Hassan et al. (2023) used the CRITIC method to determine factor weights for evaluating solar PV plant sites. Sarucan et al. (2024) ranked BSECO member countries using CRITIC, COPRAS, and Borda Count methods, with Albania ranked first. Al-Hchaimi et al. (2022) applied the CRITIC method to evaluate DoS countermeasure techniques on MPSoC-based IoT platforms. Kumar et al. (2022) utilized the CRITIC method for ranking solid-state drives in a MCDM framework. Ulutas and Karaköy (2019) analyze the performance of a cargo company from 2011 to 2017 using the CRITIC and ROV methods. Krishankumar et al. (2023) assessed zero-carbon measures in sustainable transportation within smart cities using a CRITIC-MARCOS framework based on q-rung fuzzy preferences. Günay and Ecer (2022) conducted a comparative analysis of Türkiye's real sector from both economic and financial perspectives using the CRITIC-MAIRCA method.

Yilmaz and Burdurlu (2023) prioritized criteria for selecting wooden furniture joints using the CRITIC method and ARAS method, identifying strength as the top criterion. Özekenci (2023) evaluated the export performance of Turkish metropolitan cities, ranking them using integrated MCDM methods including CRITIC. Shao et al. (2023) suggested a value index system for energy storage systems based on the CRITIC model and MCDM models. Pala (2023) compared the financial performance of technology and information sector companies using the CRITIC method for criteria weighting. Mohamed et al. (2024) used the CRITIC method to select the optimal Internet of Energy platforms for smart cities. As seen in the above studies, the CRITIC method has not been used in the Logistics 4.0 field before.

3.2 WASPAS Method

WASPAS methodology is an MCDM technique that combines the Weighted Sum Model (WSM) and the Weighted Product Model (WPM) to improve decision-making accuracy. Below are the detailed steps, explanations, and formulas (Zavadskas and Turskis, 2012):

1. Construct the Decision Matrix: The decision matrix $X = [x_{ij}]$ is formed (Equaiton 6) where x_{ij} represents the performance of alternative A_i with respect to criterion C_j.

$$X = \begin{bmatrix} x_{11} & x_{12} & x_{13} \cdots & x_{1m} \\ x_{21} & x_{22} & x_{23} & x_{2m} \\ \vdots & & \ddots & \vdots \\ x_{m1} & x_{m2} & x_{m3} \cdots & x_{mn} \end{bmatrix} \quad (6)$$

2.Normalize the Decision Matrix: Normalization is performed to transform the criteria values into a comparable scale (Equation 7 and 8).

For benefit criteria,

$$\overline{x_{ij}} = \frac{x_{ij}}{\max_i(x_{ij})} \qquad i = 1,2,\ldots.,m \qquad j = 1,2,\ldots.,n \quad (7)$$

For cost criteria,

$$\overline{x_{ij}} = \frac{\min_i(x_{ij})}{x_{ij}} \qquad i = 1,2,\ldots,m \qquad j = 1,2,\ldots,n \quad (8)$$

3. Construct the Weighted Normalized Decision Matrix: The normalized values are then multiplied by the respective weights of the criteria (Equation 9).

$$v_{ij} = w_j . r_{ij} \quad (9)$$

where w_j is the weight of criterion C_j.

4. Calculate the Overall Performance Scores Using WSM and WPM: The WSM score for each alternative A_i is calculated using Equation 10 and the WPM score for each alternative A_i is calculated using Equation 11.

$$Q_i^{(1)} = \sum_{j=1}^{n} \overline{x_{ij}} w_j \quad (10)$$

$$Q_i^{(2)} = \prod_{j=1}^{n} \overline{x_{ij}}^{w_j} \quad (11)$$

5. Combine WSM and WPM Scores: The final WASPAS score for each alternative is a combination of the WSM and WPM scores (Equaiton 12), adjusted by the parameter λ ($0 \leq \lambda \leq 1$), which balances the influence of WSM and WPM.

$$Q_i = \lambda Q_i^{(1)} + (1-\lambda) Q_i^{(2)} = \lambda \sum_{j=1}^{n} (X_{ij})\, w_j + (1-\lambda) \prod_{j=1}^{n} (X_{ij})^{w_j} \quad (12)$$

The WASPAS method has been extensively applied in various MCDM problems. Handayani et al. (2023) employed the WASPAS method to select online English courses, determining that the British Council obtained the highest score. Abualkishik and Almajed (2023) utilized WASPAS for ranking Intelligent Transportation Systems alternatives. Ahmad and Ozcek (2023) used WASPAS to solve sustainable crop selection problems using neutrosophic type 2 data. Barbara et al. (2023) developed an internet tool for decision-makers based on WASPAS, called waspasWEB. Arisantoso et al. (2023) implemented WASPAS in a decision support system for selecting webcams. Alharbi et al. (2024) assessed leadership management challenges in the energy sector using WASPAS. Mayatopani (2023) applied WASPAS for selecting corn seeds. Do (2021) optimized surface roughness and material removal rate in grinding processes using WASPAS. Narayanamoorthy et al. (2021) combined WASPAS with fuzzy set theory to select hair mask products. Taletović (2023) reviewed WASPAS among other methods for warehouse management practices.

Rastpour et al. (2022) used WASPAS to evaluate companies' greenness in the dairy industry. Akpınar (2021) used the same method to evaluate third-party logistics providers. Khalilzadeh et al. (2024) employed fuzzy WASPAS for project risk management. Zaher and Eldakhly (2023) integrated WASPAS with trapezoidal neutrosophic sets for failure mode risk evaluation. Abdelhafeez et al. (2024) ranked optimal livestock locations using WASPAS. Dahooie et al. (2022) used WASPAS for selecting solar power plant locations in Iran. Sharma et al. (2022) applied WASPAS to select lightweight materials for railway vehicles. Özekenci (2023) evaluated export performance of Turkish metropolitan cities using WASPAS. Gökkuş et al. (2023) ranked Çanakkale districts in terms of rangeland quality using WASPAS among other methods. Pala (2023) compared the financial performance of technology companies using WASPAS. Akmermer and Çelik (2021) evaluated the contribution of fishery products to Turkish foreign trade using WASPAS. Aytekin et al. (2023) evaluated pharmaceutical distribution and warehousing companies using a combined Fermatean fuzzy Entropy-WASPAS approach. Karaca and Ulutaş (2018) use Entropy and WASPAS methods to select the most suitable renewable energy source for Türkiye. By analyzing multiple energy alternatives, the study provides a comprehensive evaluation model that ranks energy sources based on various criteria. As seen in the above studies, the WASPAS method has not been used in the Logistics 4.0

field before, too. Therefore, this study plans to take its place in the literature as the first study in which the CRITIC and WASPAS methods are used as a hybrid in the field of Logistics 4.0.

The CRITIC and WASPAS methods were specifically chosen for this study due to their unique advantages in MCDM. The CRITIC method allows for the determination of objective weights for criteria, minimizing the potential biases associated with subjective judgments. The WASPAS method, which combines the WSM and WPM, enhances decision accuracy by considering both additive and multiplicative factors. These methods were deemed particularly suitable for Logistics 4.0 service provider evaluation, where multiple interrelated criteria must be considered. Compared to alternative methods, the integration of CRITIC and WASPAS offers a more comprehensive and reliable approach for addressing the complexity of Logistics 4.0 decision-making.

4. PROBLEM STATEMENT USING MCDM

With the emergence of the concept of Logistics 4.0, businesses are turning to work with companies that have proven themselves in this field and to increase their collaborations. This situation necessitates the transformation of many logistic companies in this field. In this study, the problem of a company deciding on the most suitable among alternative companies that have implemented Logistics 4.0 among logistics service providers and proven themselves in this field was addressed. In the problem addressed, five alternative logistics companies were determined by the purchasing experts of the company. Ten criteria were determined for the evaluation of these alternatives. The criteria used in this study, such as operational efficiency, technological infrastructure, and real-time monitoring, are directly related to improving logistics efficiency. The integration of these criteria into the CRITIC-WASPAS framework ensures that the selected service providers are those most capable of optimizing logistical processes and achieving higher levels of efficiency. The evaluation criteria used in this study were selected based on a comprehensive review of the relevant literature in the field of Logistics 4.0 and MCDM. Key criteria, such as technological infrastructure, operational efficiency, and sustainability, were chosen because they are critical success factors in the implementation of Logistics 4.0 systems. Moreover, expert consultations with industry professionals ensured that the selected criteria reflect the most important aspects of logistics service provider performance in today's digital and automated environments. According to the criteria addressed, the alternative that best provides the Logistics 4.0 transformation was selected. The problem hierarchy is provided in Figure 1. The criteria used in the study are as follows:

Technological Infrastructure (TI): The level of IoT, big data analytics, artificial intelligence, and automation systems that the company possesses.

Integration Capability (IC): The company's ability to integrate with existing supply chain and logistics processes. This includes compatibility with ERP (Enterprise Resource Planning) and other logistics software.

Data Security and Privacy (DSP): The company's data security policies and measures are taken to ensure data privacy.

Real-Time Monitoring and Visibility (RTMV): The company's ability to provide real-time monitoring and visibility at every stage of logistics process and the supply chain.

Adaptability and Flexibility (AF): The company's capacity to quickly adapt to changing market conditions and customer demands.

Operational Efficiency (OE): How efficiently the company manages its processes, its success in reducing costs, and optimizing operations.

Customer Service and Support (CSS): The quality of the company's customer service and technical support.

Logistics Network and Coverage (LNC): The company's logistics network and coverage area, including which regions it serves and its performance in those regions.

Environmental Sustainability (ES): The company's environmental sustainability policies and practices.

References and Reputation (RR): The company's reputation in the industry, customer references, and past performance.

The decision matrix was created after the decision-makers determined the criteria mentioned above. The decision matrix used in the study is given in Table 1. Normalized decision matrix is provided in Table 2 while a correlation matrix is provided in Table 3. Standard deviation, information content calculation, and weight results are provided in Table 4.

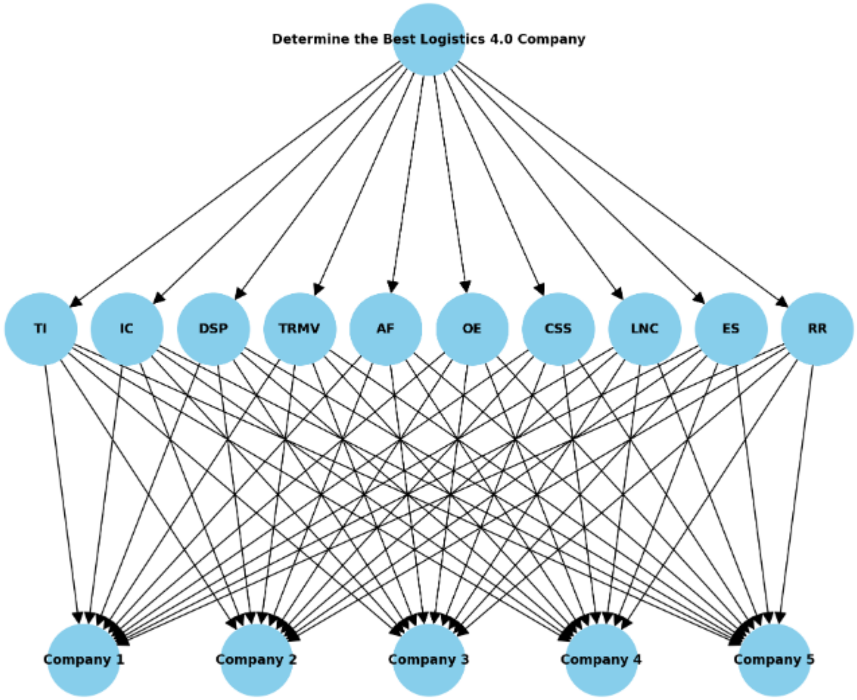

Figure 1: The hierarchical structure of the problem

Table 1. Decision matrix of the problem

Criteria	*TI*	*IC*	*DSP*	*TRMV*	*AF*	*OE*	*CSS*	*LNC*	*ES*	*RR*
Company 1	45	55	40	40	60	55	50	45	90	60
Company 2	55	35	45	30	45	75	35	30	40	50
Company 3	85	80	80	75	85	70	70	90	85	25
Company 4	80	85	75	90	80	95	90	85	65	20
Company 5	65	70	65	70	75	60	55	60	70	40

Table 2. Normalized matrix

Criteria	*TI*	*IC*	*DSP*	*TRMV*	*AF*	*OE*	*CSS*	*LNC*	*ES*	*RR*
Company 1	0.000	0.400	0.000	0.167	0.375	0.000	0.273	0.250	1.000	0.000
Company 2	0.250	0.000	0.125	0.000	0.000	0.500	0.000	0.000	0.000	0.250
Company 3	1.000	0.900	1.000	0.750	1.000	0.375	0.636	1.000	0.900	0.875
Company 4	0.875	1.000	0.875	1.000	0.875	1.000	1.000	0.917	0.500	1.000
Company 5	0.500	0.700	0.625	0.667	0.750	0.125	0.364	0.500	0.600	0.500

Table 3. Correlation matrix

Criteria	*TI*	*IC*	*DSP*	*TRMV*	*AF*	*OE*	*CSS*	*LNC*	*ES*	*RR*
TI	1.000	0.809	0.981	0.860	0.827	0.595	0.786	0.912	0.095	0.978
IC	0.809	1.000	0.881	0.969	0.978	0.356	0.927	0.960	0.516	0.828
DSP	0.981	0.881	1.000	0.920	0.905	0.491	0.805	0.938	0.196	0.960
TRMV	0.860	0.969	0.920	1.000	0.932	0.508	0.929	0.928	0.291	0.905
AF	0.827	0.978	0.905	0.932	1.000	0.226	0.840	0.960	0.563	0.804
OE	0.595	0.356	0.491	0.508	0.226	1.000	0.633	0.432	-0.469	0.715
CSS	0.786	0.927	0.805	0.929	0.840	0.633	1.000	0.909	0.334	0.857
LNC	0.912	0.960	0.938	0.928	0.960	0.432	0.909	1.000	0.458	0.897
ES	0.095	0.516	0.196	0.291	0.563	-0.469	0.334	0.458	1.000	0.019
EE	0.978	0.828	0.960	0.905	0.804	0.715	0.857	0.897	0.019	1.000

Table 4. Final weights

Criteria	*TI*	*IC*	*DSP*	*TRMV*	*AF*	*OE*	*CSS*	*LNC*	*ES*	*RR*
σ_j	0.418	0.406	0.445	0.418	0.409	0.389	0.380	0.427	0.394	0.418
C_j	0.903	0.722	0.857	0.736	0.804	2.146	0.753	0.686	2.755	0.853
W_j	0.081	0.064	0.076	0.066	0.072	0.191	0.067	0.061	0.246	0.076

In the study, the calculation phase of the criteria weights with the CRITIC method was concluded with Table 4. It was seen that the criterion with the highest weight was the ES criterion. The criterion with the lowest level of importance was the LNC criterion. The ranking of the alternatives was made with the WASPAS method. First, the normalized values are shown in Table 5. Total relative importance values are provided in Table 6 while total relative importance by WPM values are provided in Table 7.

Table 5. Normalized matrix

Criteria	*TI*	*IC*	*DSP*	*TRMV*	*AF*	*OE*	*CSS*	*LNC*	*ES*	*RR*
Company 1	0.529	0.647	0.500	0.444	0.706	0.579	0.556	0.500	1.000	0.333
Company 2	0.647	0.412	0.563	0.333	0.529	0.789	0.389	0.333	0.444	0.400
Company 3	1.000	0.941	1.000	0.833	1.000	0.737	0.778	1.000	0.944	0.800
Company 4	0.941	1.000	0.938	1.000	0.941	1.000	1.000	0.944	0.722	1.000
Company 5	0.765	0.824	0.813	0.778	0.882	0.632	0.611	0.667	0.778	0.500

Table 6. Total relative importance (Q1)

Criteria	*TI*	*IC*	*DSP*	*TRMV*	*AF*	*OE*	*CSS*	*LNC*	*ES*	*RR*
Company 1	0.043	0.041	0.038	0.029	0.051	0.111	0.037	0.031	0.246	0.025
Company 2	0.052	0.026	0.043	0.022	0.038	0.151	0.026	0.020	0.109	0.030
Company 3	0.081	0.060	0.076	0.055	0.072	0.141	0.052	0.061	0.232	0.061
Company 4	0.076	0.064	0.071	0.066	0.068	0.191	0.067	0.058	0.178	0.076
Company 5	0.062	0.053	0.062	0.051	0.064	0.121	0.041	0.041	0.191	0.038

Table 7. Total relative importance by WPM (Q2)

Criteria	*TI*	*IC*	*DSP*	*TRMV*	*AF*	*OE*	*CSS*	*LNC*	*ES*	*RR*
Company 1	0.950	0.973	0.949	0.948	0.975	0.901	0.961	0.959	1.000	0.920
Company 2	0.965	0.945	0.957	0.930	0.955	0.956	0.939	0.935	0.819	0.933
Company 3	1.000	0.996	1.000	0.988	1.000	0.943	0.983	1.000	0.986	0.983
Company 4	0.995	1.000	0.995	1.000	0.996	1.000	1.000	0.997	0.923	1.000
Company 5	0.979	0.988	0.984	0.984	0.991	0.916	0.968	0.976	0.940	0.949

Q_i values for Company 1 is 0.635, Company 2 is 0.508, Company 3 is 0.888, Company 4 is 0.911, and Company 5 is 0.719 respectively. Hence the best alternative is Company 4 with the highest score. After, Company 3, Company 5, Company 1, and Company 2 are the other selectable alternatives.

5. DISCUSSION and CONLUSION

Industry 4.0 represents the fourth industrial revolution, marked by the integration of advanced digital technologies into manufacturing processes. It combines the Internet of Things, artificial intelligence, big data analytics, and cyber-physical systems to create smart factories. These technologies are also pivotal in transforming logistics, leading to the emergence of Logistics 4.0. In smart factories, interconnected machines communicate and make autonomous decisions, impacting supply chain logistics by improving efficiency and productivity. Industry 4.0 enhances flexibility and customization in production, which in turn demands more agile and responsive logistics systems. Data-driven decision-making, predictive maintenance, and real-time monitoring are critical components that improve logistics operations. By leveraging cloud computing and edge computing, Industry 4.0 enables seamless data exchange across the entire supply chain, enhancing logistics coordination. The revolution fosters innovation through digital twins, virtual simulations, and augmented reality, which are also applied in logistics for better planning and execution. Cybersecurity becomes crucial to protect interconnected systems, including logistics networks, from potential threats. Overall, Industry 4.0 is transforming traditional manufacturing and logistics into highly automated, intelligent, and adaptive ecosystems.

Logistics 4.0 is the application of Industry 4.0 principles to the logistics and supply chain management sector. It leverages IoT, AI, big data, and automation to streamline logistics operations. Smart logistics systems enable real-time tracking and monitoring of goods, enhancing visibility and transparency. AI algorithms optimize routing and scheduling, reducing delivery times and costs. Autonomous vehicles and drones are increasingly used for transportation and warehousing, minimizing human intervention. Predictive analytics helps in demand forecasting and inventory management, ensuring efficient stock levels. The integration of blockchain technology ensures secure and transparent transactions. Collaborative robots (cobots) assist in warehouse operations, improving accuracy and speed. Logistics 4.0 promotes sustainability by optimizing routes and reducing emissions. It creates interconnected and flexible supply chains that can quickly respond to market demands. The results of this study demonstrate that the selected logistics service providers, particularly those ranked highest, offer significant opportunities for improving operational efficiency. By utilizing advanced technologies and optimizing key performance indicators such as flexibility and adaptability, these providers contribute to more efficient and responsive logistics operations, aligning with the goals of Logistics 4.0.

To select the best Logistics 4.0 service provider, the CRITIC and WASPAS methods were employed in this study. These MCDM methods allowed for a comprehensive evaluation of each company based on the ten criteria. The CRITIC method helped in determining the objective weights of the criteria by considering the contrast intensity of each criterion. The WASPAS method combined the WSM and the WPM, providing a robust framework for ranking the alternatives. Through this approach, the most suitable company was selected based on its overall performance across the evaluated criteria. Finally, this study successfully identified the best company for Logistics 4.0 implementation using a structured and rigorous evaluation process. This study makes significant contributions to the field by introducing the combined use of CRITIC and WASPAS methods in the evaluation of Logistics 4.0 service providers. By integrating these two powerful MCDM techniques, the study fills a notable gap in the literature, where objective and systematic approaches to service provider selection in Logistics 4.0 are limited. The combined methodology offers valuable insights for both academic research and practical applications in the logistics industry, providing a robust framework for more reliable decision-making. Future studies could explore the integration of additional criteria, such as the company's innovation capacity and collaboration with technology partners. Moreover, applying other MCDM methods and comparing their results could provide further insights into the robustness of the selection process. Moreover, longitudinal studies could be conducted to assess the long-term impact of Logistics 4.0 implementation on the selected company's performance.

Conflict of Interest
No potential conflict of interest was declared by the author.

Funding
Any specific grant has not been received from funding agencies in the public, commercial, or not-for-profit sectors.

Compliance with Ethical Standards
It was declared by the author that the tools and methods used in the study do not require the permission of the Ethics Committee.

Ethical Statement
It was declared by the author that scientific and ethical principles have been followed in this study and all the sources used have been properly cited.

REFERENCES

Abdelhafeez, A., Khalil, N. A., Eassa, M., & Elkholy, M. (2024). “Selection Optimal Livestock Location under Multi-Criteria Decision Making Fuzzy Framework”. *Precision Livestock*, *1*, 58-65.

Abouhawwash, M. and Jameel, M. (2023). “Evaluation Factors of Solar Power Plants to Reduce Cost Under Neutrosophic Multi-Criteria Decision Making Model”, *Sustainable Management Journal*, 2(3), 101-114.

Abualkishik, A. and Almajed, R. (2023). “WASPAS Multi-Criteria Decision-Making Method for Assessment Effectiveness and Performance Intelligent Transportation Systems Alternatives”, *Financial Technology & Innovation*, 3(1), 1-12.

Agyabeng-Mensah, Y., Ahenkorah, E., Afum, E., Owusu, L., Agyabeng, C. and Baah, C. (2020). “The Influence of Logistics Outsourcing, Information Technology, and Innovation Capabilities on Supply Chain Sustainability”, *Journal of Cleaner Production*, 258, 120808. https://doi.org/10.1016/j.jclepro.2020.120808

Ahmad, A. and Ozcek, M. (2023). “Multi-Criteria Decision-Making Methodology for Sustainable Crop Selection”, *International Journal of Artificial Intelligence and Computing*, 6(1), 1-15.

Ahmad, U., Khan, A. and Saeid, A. (2023). “Integrated Multi-Criteria Group Decision-Making Methods Based on Q-Rung Picture Fuzzy Sets for the Identification of Occupational Hazards”, *Applied Soft Computing*, 123, 105591.

Akmermer, B., & Çelik, P. (2021). “Contribution of fishery and aquaculture products to Turkish foreign trade: An evaluation by a hybrid multi-criteria decision-making method”. *Ege Journal of Fisheries & Aquatic Sciences (EgeJFAS)/Su Ürünleri Dergisi*, *38*(3).

Akpınar, M. E. (2021). “Third-party logistics (3PL) provider selection using hybrid model of SWARA and WASPAS”. *International Journal of Pure and Applied Sciences*, *7*(3), 371-382.

Alharbi, A.H., Jabali, H.M., Rajan, P. and Salamai, A. (2024). “Evaluation Challenges of Leadership Management in the Energy Sector using Multi-Criteria Decision Making Approach”, *Management Studies*, 4(2), 21-30.

Al-Hchaimi, A.A.J., Sulaiman, N.B., Mustafa, M.A.B, Mohtar, M.N.B, Hassan, S.L.B.M. and Muhsen, Y.R. (2022). “Evaluation Approach for Efficient Countermeasure Techniques Against Denial-of-Service Attack on MPSoC-Based IoT Using Multi-Criteria Decision-Making”, *IEEE Access*, 10, 114569-114585. https://doi.org/10.1109/ACCESS.2022.3232395

Arisantoso, A., Somaida, M.H., Sanwasih, M. and Shalahudin, M.I. (2023). “Multi-Criteria Decision Making Using the WASPAS Method in Webcam Selection Decision Support Systems”, *Indonesian Journal of Computing Science*, 7(1), 1-11.

Aytekin, A., Görçün, Ö.F., Ecer, F., Pamucar, D. and Karamaşa, Ç. (2023). “Evaluation of the Pharmaceutical Distribution and Warehousing Companies through An Integrated Fermatean Fuzzy Entropy-WASPAS Approach”, *Kybernetes*, 52(11), 5561-5592.

Barbara, F., dos Santos, M., Silva, A.S., Moreira, M., Lopes Fávero, L.P., Pereira Júnior, E.L., Carvalho, W.A., Muradas, F., Pereira, D.A. de M. and Portella, A.G. (2023). “Interactive Internet Framework Proposal of WASPAS Method: A Computational Contribution for Decision-Making Analysis”, *Mathematics*, 11(15), 3375.

Barreto, L., Amaral, A. and Pereira, T. (2017). “Industry 4.0 Implications in Logistics: An Overview”, *Procedia Manufacturing*, 13, 1245-1252.

Büyüközkan, G. and Göçer, F. (2018). “Digital Supply Chain: Literature Review and A Proposed Framework for Future Research”, *Computers in Industry*, 97, 157-177. https://doi.org/10.1016/j.compind.2018.02.010

Choi, T.M., Chan, H.K. and Yue, X. (2019). “Recent Development in Big Data Analytics for Business Operations and Risk Management”, *IEEE Transactions on Cybernetics*, 49(1), 36-45.

de Oliveira, U.R. and Handfield, R. (2019). “Analytical Models for Assessing Green Supply Chain Practices in the Brazilian Automotive Industry”, *Resources, Conservation and Recycling*, 145, 269-278. https://doi.org/10.1016/j.resconrec.2019.02.031

Diakoulaki, D., Mavrotas, G. and Papayannakis, L. (1995). “Determining Objective Weights in Multiple Criteria Problems: The CRITIC Method”, *Computers & Operations Research*, 22(7), 763-770. https://doi.org/10.1016/0305-0548(94)00059-H

Do, T. (2021). “The Combination of Taguchi – Entropy – WASPAS - PIV Methods for Multi-Criteria Decision Making When External Cylindrical Grinding of 65G Steel”, *Journal of Manufacturing Engineering*, 14, 1-12.

Fottler, M., Ford, E. and Braunscheidel, M. (2020). “Healthcare Operations Management: A Systems Perspective”, Routledge. https://doi.org/10.4324/9781003046778

Gökkuş, Z., Şentürk, S., & Alatürk, F. (2023). “Ranking Çanakkale Districts in terms of rangeland quality with multi-criteria decision making methods”. *Türk Tarım ve Doğa Bilimleri Dergisi*, *10*(3), 605-614.

Govindan, K., Soleimani, H. and Kannan, D. (2018). “Reverse Logistics and Closed-Loop Supply Chain: A Comprehensive Review to Explore the Future”, *European Journal of Operational Research*, 240(3), 603-626.

Günay, F. and Ecer, F. (2022). "A Comparative Analysis of the Real Sector in Turkey from the Economic and Financial Perspectives with the CRITIC-MAIRCA Method", *Ekonomi Politika ve Finans Araştırmaları Dergisi*, 7(1), 186-219.

Handayani, N., Heriyani, N., Septian, F. and Alexander, A.D. (2023). "Multi-Criteria Decision Making Using the WASPAS Method for Online English Course Selection", *Teknoinfo*, 17(1), 1-10.

Hassan, I., Alhamrouni, I. and Azhan, N.H. (2023). "A CRITIC–TOPSIS Multi-Criteria Decision-Making Approach for Optimum Site Selection for Solar PV Farm", *Energies*, 16(10), 4245.

Heidary Dahooie, J., Husseinzadeh Kashan, A., Shoaei Naeini, Z., Vanaki, A.S., Zavadskas, E.K. and Turskis, Z. (2022). "A Hybrid Multi-Criteria-Decision-Making Aggregation Method and Geographic Information System for Selecting Optimal Solar Power Plants in Iran". *Energies*, *15*(8), 2801.

Hofmann, E. and Rüsch, M. (2017). "Industry 4.0 and the Current Status as well as Future Prospects on Logistics", *Computers in Industry*, 89, 23-34.

Ivanov, D., Dolgui, A. and Sokolov, B. (2019). "The Impact of Digital Technology and Industry 4.0 on the Ripple Effect and Supply Chain Risk Analytics", *International Journal of Production Research*, 57(3), 829-846.

Kannan, D., Govindan, K. and Rajendran, S. (2020). "Fuzzy AHP Integrated with Fuzzy TOPSIS for Analyzing Logistics Service Provider Selection Criteria", *Journal of Cleaner Production*, 106, 256-267. https://doi.org/10.1016/j.jclepro.2014.11.053

Karaca, C. and Ulutaş, A. (2018). "Entropi ve WASPAS Yöntemleri Kullanılarak Türkiye Için Uygun Yenilenebilir Enerji Kaynağının Seçimi", *Ege Academic Review*, 18(3), 483-494.

Khalilzadeh, M., Banihashemi, S.A. and Božanić, D. (2024). "A Step-by-Step Hybrid Approach Based on Multi-Criteria Decision-Making Methods and A Bi-Objective Optimization Model to Project Risk Management", *Decision Making in Manufacturing and Services*, 7(1), 1-15.

Krishankumar, R., Mishra, A.R., Rani, P., Ecer, F. and Ravichandran, K.S. (2023). "Assessment of Zero-Carbon Measures for Sustainable Transportation in Smart Cities: A CRITIC-MARCOS Framework Based on Q-Rung Fuzzy Preferences", *IEEE Internet of Things Journal,* 10(21), 18651-1866. https://doi.org/10.1109/JIOT.2023.3293513

Kumar, R., Goel, P., Zavadskas, E., Stević, Ž. and Vujović, V. (2022). "A New Joint Strategy for Multi-Criteria Decision-Making: A Case Study for Prioritizing Solid-State Drive", *International Journal of Computers Communications & Control*, 17(6), 5010.

Lai, H. and Liao, H. (2021). "A Multi-Criteria Decision Making Method Based on DNMA and CRITIC with Linguistic D Numbers for Blockchain Platform Evaluation", *Engineering Applications of Artificial Intelligence*, 95, 104200.

Mayatopani, H. (2023). "Multi-Criteria Decision Making Using Weighted Aggregated Sum Product Assessment in Corn Seed Selection System", *Cereal International*, 15, 21-31.

Mohamed, M., Ayman, S. and Sleem, A. (2024). "Valuation of Internet of Energy (IoE) Platforms in Smart Cities: A Hybrid Multi-Criteria Decision Making Approach", *Plant Cell Biotechnology and Molecular Biology*, 25(3), 253-264.

Nabavi, S., Wang, Z. and Rangaiah, G.P. (2024). "Sensitivity Assessment of Multi-Criteria Decision-Making Methods in Chemical Engineering Optimization Applications", arXiv preprint.

Narayanamoorthy, S., Brainy, J.V., Manirathinam, T., Kalaiselvan, S., Kureethara, J.V. and Kang, D. (2021). "An Adoptable Multi-Criteria Decision-Making Analysis to Select a Best Hair Mask Product-Extended Weighted Aggregated Sum Product Assessment Method", *Fuzzy Information and Engineering*, 7(1), 1-10.

Özekenci, E.K. (2023). "Evaluation of Export Performances of Metropolitans in Turkey Based on Integrated Multi-Criteria Decision-Making Methods", *Dicle University Journal of Economics and Administrative Sciences*, 14(1), 59-74.

Pala, F. (2023). "Comparison of the Companies Operated for Technology and Information Sector in BIST by Multi-Criteria Decision Making Method and Financial Performance Measurements", *Financial Studies*, 27(1), 117-130.

Rastpour, E., Kayvanfar, V. and Rafiee, M. (2022). Multi-Criteria Decision-Making Methods for the Evaluating of A Real Green Supply Chain in Companies with Fast-Moving Consumer Goods", *International Journal of Production Research*, 1, 1-14.

Saarikko, T., Westergren, U.H. and Blomquist, T. (2020). "Digital Transformation: Five Recommendations for the Digitally Conscious Firm", *Business Horizons*, 63(6), 825-839. https://doi.org/10.1016/j.bushor.2020.07.005

Sarucan, A., Baysal, M.E. and Engin, O. (2024). "Ranking of the Member Countries in the Black Sea Economic Cooperation Organization Using Multi-Criteria Decision-Making Methods", *Journal of Sustainable Development*, 19(1), 101-113.

Shao, C., Wei, B., Liu, W., Yang, Y., Zhao, Y. and Wu, Z. (2023). "Multi-Dimensional Value Evaluation of Energy Storage Systems in New Power System Based on Multi-Criteria Decision-Making", *Processes*, 11(5), 1565.

Sharma, M., Luthra, S., Joshi, S., & Kumar, A. (2022). "Developing a framework for enhancing survivability of sustainable supply chains during and post-COVID-19 pandemic". *International Journal of Logistics Research and Applications*, *25*(4-5), 433-453.

Taletović, M. (2023). “Application of Multi-Criteria Decision-Making Methods in Warehouse: A Brief Review”, *Studies in Economics and Management*, 11, 31-45.

Ulutaş, A. and Karaköy, Ç. (2019). “CRITIC ve ROV Yöntemleri Ile Bir Kargo Firmasının 2011-2017 Yılları Sırasındaki Performansının Analiz Edilmesi”, *MANAS Sosyal Araştırmalar Dergisi*, 8(1), 223-230.

Wang, G., Gunasekaran, A., Ngai, E.W. and Papadopoulos, T. (2020). “Big Data Analytics in Logistics and Supply Chain Management: Certain Investigations for Research and Applications”, *International Journal of Production Economics*, 176, 98-110.

Yazdani, M., Chatterjee, P., Zavadskas, E.K. and Streimikiene, D. (2019). “A Novel Integrated Decision-Making Approach for the Evaluation and Selection of Sustainable Suppliers in the Power Industry”, *Sustainability*, 10(1), 1-19. https://doi.org/10.3390/su10010015

Yilmaz, K. and Burdurlu, E. (2023). “Selection of Wooden Furniture Joints with Multi-Criteria Decision-Making Techniques”, *International Journal of Computer Integrated Manufacturing*, 36(8), 842-856.

Zaher, M. A., & Eldakhly, N. M. (2023). “An Integrated Framework for Dynamic Resource Allocation in Multi-project Environment”. *Full Length Article*, 10(1), 08-8.

Zavadskas, E.K. and Turskis, Z. (2012). “A New Additive Ratio Assessment (ARAS) Method in Multicriteria Decision-Making”, *Technological and Economic Development of Economy*, 16(2), 159-172.

Zavadskas, E.K., Turskis, Z. and Kildienė, S. (2012). “State of Art Surveys of Overviews on MCDM/MADM Methods”, *Technological and Economic Development of Economy*, 18(4), 672-695.

Zhang, X., Lv, M. and Yuan, X. (2023). “Research on Cloud-CRITIC-PDR Method for Hybrid Multi-Criteria Decision Making”, *Journal of Intelligent & Fuzzy Systems*, 45, 5067-5078.

VERİMLİLİK DERGİSİ
JOURNAL OF PRODUCTIVITY

Evaluation of Machine Learning and Ensemble Learning Models for Classification Using Delivery Data

İrem Karakaya[1]

ABSTRACT

Purpose: This study aims to evaluate the performance of various machine learning and ensemble learning models in classifying delivery times using Amazon delivery data. Fast deliveries' role in providing a competitive advantage and boosting customer loyalty highlights the importance of this study.

***Methodology*:** The research employs a dataset of 43,739 delivery records with 15 features. Data preprocessing steps include handling missing values, encoding categorical variables, calculating geospatial distances, and normalizing data. Advanced machine learning techniques (e.g., KNN, SVM, Logistic Regression) and ensemble methods (e.g., ExtraTrees, AdaBoost) were systematically compared based on accuracy, precision, recall, and F-score.

Findings: Ensemble learning models, particularly those using SVM, NB, and LDA as base models and ET as the meta model, achieved the highest accuracy (99.89%) and F-score (99.89%). These results underscore the potential of such models to optimize logistics operations, reduce delays, and enhance customer satisfaction.

Originality: This study demonstrates the effectiveness of machine and ensemble learning methods on complex logistics data, contributing to optimizing logistics efficiency and enhancing customer satisfaction. Additionally, the application of ensemble learning methods on complex and large-scale logistics data structures is unique in terms of its contribution to the literature. The proposed framework offers a scalable solution for real-time predictive modeling and logistics optimization.

Keywords*:* Machine Learning, Ensemble Learning, Logistics Optimization, E-Commerce Logistics.
JEL Codes: C45, L81, L91.

Teslimat Verileri Kullanılarak Makine Öğrenimi ve Topluluk Öğrenme Modelleri ile Sınıflandırma Performansının Değerlendirilmesi

ÖZET

Amaç: Bu çalışma, Amazon teslimat verilerini kullanarak çeşitli makine öğrenimi ve topluluk öğrenme modellerinin teslimat sürelerini sınıflandırma performansını değerlendirmeyi amaçlamaktadır. Hızlı teslimatların rekabet avantajı sağlamadaki ve müşteri sadakatini artırmadaki rolü, bu çalışmanın önemini vurgulamaktadır.

***Yöntem*:** Araştırmada, 15 özelliğe sahip 43.739 teslimat kaydından oluşan bir veri seti kullanılmaktadır. Veri ön işleme adımları, eksik değerlerin işlenmesi, kategorik değişkenlerin kodlanması, coğrafi mesafelerin hesaplanması ve verilerin normalleştirilmesini içermektedir. Gelişmiş makine öğrenimi teknikleri (örneğin, KNN, SVM, Lojistik Regresyon) ve topluluk yöntemleri (örneğin, ExtraTrees, AdaBoost), doğruluk, hassasiyet, geri çağırma ve F-skoru gibi metrikler temel alınarak sistematik bir şekilde karşılaştırılmıştır.

Bulgular: Topluluk öğrenme modelleri, özellikle temel model olarak SVM, NB ve LDA ile üst model olarak ET kullanıldığında en yüksek doğruluk (%99.89) ve F-skoru (%99.89) değerlerine ulaşmıştır. Bu sonuçlar, bu tür modellerin lojistik operasyonlarını optimize etme, gecikmeleri azaltma ve müşteri memnuniyetini artırma potansiyelini vurgulamaktadır.

Özgünlük: Bu çalışma, makine ve topluluk öğrenme yöntemlerinin karmaşık lojistik verilerdeki etkinliğini göstererek, lojistik verimliliğin optimize edilmesine ve müşteri memnuniyetinin artırılmasına katkı sağlamaktadır. Ayrıca, karmaşık ve geniş ölçekli lojistik veri yapıları üzerinde topluluk öğrenme yöntemlerinin uygulanmasının literatüre yaptığı katkı açısından benzersizdir. Önerilen çerçeve, gerçek zamanlı tahmin modelleme ve lojistik optimizasyonu için ölçeklenebilir bir çözüm sunmaktadır.

Anahtar Kelimeler*:* Makine Öğrenimi, Topluluk Öğrenme, Lojistik Optimizasyonu, E-Ticaret Lojistiği.
JEL Kodları: C45, L81, L91.

[1]Bartın Üniversitesi, Bartın Meslek Yüksekokulu, Yönetim ve Organizasyon Bölümü, Bartın, Türkiye

Corresponding Author: İrem Karakaya, isahmutoglu@bartin.edu.tr

DOI: 10.51551/verimlilik.1526436
Research Article | Submitted: 01.08.2024 | Accepted: 07.01.2025
Cite: Karakaya, İ. (2025). "Evaluation of Machine Learning and Ensemble Learning Models for Classification Using Delivery Data", *Verimlilik Dergisi,* Productivity for Logistics (SI), xxx-xxx.

1. INTRODUCTION

In today's rapidly digitalizing world, the e-commerce sector plays a pivotal role in transforming retail sales and necessitating the optimization of logistics processes. With the growth of the e-commerce industry, accurately and swiftly predicting delivery times has become critically important for customer satisfaction and business efficiency. The complexity of logistics operations and increasing customer demands require the analysis of large datasets that traditional methods cannot manage (Tsang et al., 2021). Major e-commerce platforms place significant emphasis on optimizing the accuracy and efficiency of delivery times to enhance customer satisfaction and gain a competitive edge. Machine learning algorithms are crucial in making logistics processes more efficient due to their ability to make effective predictions on large and complex datasets. In this context, machine learning algorithms offer revolutionary solutions in logistics and supply chain management through their capabilities to process large datasets and model complex relationships (Tsolaki et al., 2023).

Accurately predicting delivery times in e-commerce logistics poses various challenges. These challenges arise from the complexity of logistics operations, which involve numerous variables such as traffic conditions, weather disruptions, warehouse processing times, and last-mile delivery inefficiencies (Eskandaripour and Boldsaikhan, 2023). Last-mile delivery, often regarded as the most resource-intensive segment, is further complicated by urban congestion and unpredictable customer availability. These challenges highlight the need for robust predictive models capable of handling large-scale, heterogeneous datasets. Traditional forecasting methods struggle to account for these dynamic and often unpredictable factors, leading to delays and inaccuracies in delivery estimations. Inaccurate predictions result in customer dissatisfaction, increased operational costs, and a loss of competitive advantage in the highly competitive e-commerce environment. Therefore, finding reliable solutions to improve the accuracy of delivery time predictions is critical for enhancing customer satisfaction, optimizing resources, and ensuring the overall efficiency of logistics processes.

In this study, a series of machine learning models were tested to classify delivery times using Amazon delivery data. The obtained results were compared to determine which model provided the most effective performance in this field. At the end of the study, a comprehensive evaluation of the effectiveness of the analysis methods and selected machine learning models is presented. This aims to identify the most suitable and effective machine learning model for optimizing delivery times in the retail sector. Additionally, this research is intended to make significant contributions to the utilization of datasets and the optimization of machine learning models in the fields of retail product logistics and last-mile transportation. The findings underscore the potential for advanced data-driven approaches to transform logistics efficiency and customer satisfaction.

Despite the existence of various studies in the current literature on predicting delivery times in e-commerce logistics, previous studies have predominantly been conducted using smaller datasets and limited model combinations. For instance, studies by Kazan and Karakoca (2019) and Khiari and Olaverri-Monreal (2020) used relatively small datasets with limited model diversity. This study addresses these limitations by leveraging a large-scale dataset from Amazon, incorporating diverse features, and applying a comprehensive range of machine learning and ensemble learning models. Research employing large-scale datasets and a wide range of algorithms is relatively scarce. This study seeks to fill this gap by conducting a comprehensive analysis of large-scale Amazon delivery data through the application of machine learning and ensemble learning methods. The objective is to address the limitations of traditional models in accurately predicting delivery times, particularly when faced with the complexities of large-scale, dynamic logistics data. By improving delivery time predictions, e-commerce platforms can gain a competitive edge and better meet growing customer demands. Key research questions include:

1) How can machine learning and ensemble learning models improve the accuracy of delivery time predictions?
2) Which model performs best across various logistics scenarios?
3) Which is the most effective model when the performance of methods is systematically compared with the aim of improving the efficiency of logistics processes?

In this study, the methodologies for big data analysis were meticulously selected in alignment with established successful applications in the literature. As highlighted by Bruni et al. (2023) and Salari et al. (2022), essential data preprocessing steps, including imputing missing values, transforming categorical variables, and feature extraction, were systematically implemented. For the deployment of machine learning models, widely adopted algorithms such as KNN, SVM, Naive Bayes, and Random Forest were utilized. Furthermore, ensemble learning methods were employed through the use of bagging, boosting, and stacking techniques, following the recommendations of prior Research (Karakaya et al., 2022). The effectiveness of these models was evaluated based on key performance metrics such as accuracy, precision, and F-score to ensure the robustness of the predictions. These methodologies are intended to enhance the efficiency of logistics processes.

1.1. Contributions

This study demonstrates the effectiveness of machine learning and ensemble learning models in classifying delivery times using real-world data from Amazon, addressing a critical gap in the literature where large-scale logistics datasets have been underexplored. By leveraging advanced preprocessing techniques and conducting a comparative analysis of 12 machine learning and ensemble learning models, the study provides a robust framework for improving delivery time predictions. Key contributions include:

Practical Applications: The study highlights how ensemble learning methods, specifically combining SVM, NB, and LDA with ET, can significantly enhance efficiency, reduce costs, and improve customer satisfaction in e-commerce logistics.

Methodological Insights: The research showcases advanced feature engineering techniques, such as timestamp transformations and geospatial distance calculations, to optimize data for machine learning applications.

Comprehensive Evaluation: The findings offer a detailed comparative analysis of multiple models, establishing ensemble learning methods as superior for complex logistics data.

Generalizability: While focusing on Amazon delivery data, the study's methodology and insights are applicable to other logistics and supply chain scenarios, including last-mile delivery, inventory management, and network optimization.

This research sets a foundation for the broader adoption of machine learning and ensemble learning models in logistics, providing actionable insights for both academic and industrial applications. By addressing the challenges associated with complex, large-scale logistics data, the study contributes to enhancing operational efficiency and meeting the growing demands of e-commerce.

1.2. Organization

This study is organized as follows: Section 1 provides the motivation, purpose, contrubutions, and significance of the study. Section 2 summarizes previous research on machine learning and ensemble learning in logistics. Section 3 describes the dataset, preprocessing steps, and details of the machine learning and ensemble learning models used. Section 4 presents the performance metrics and results of the models, including accuracy, precision, recall, and F-score. Section 5 analyzes the findings, compares model performances, and discusses the implications for logistics optimization. Finally, Section 6 summarizes the study's contributions, results, and potential future work.

2. LITERATURE REWIEV

Leveraging machine learning and ensemble learning methods to support areas such as delivery times and customer satisfaction holds significant importance in modern logistics and retail sectors. Studies in these fields provide data-driven approaches to enhance operational efficiency, improve customer satisfaction, and optimize logistics processes. This section presents summaries of literature, showcasing the key findings and results of various studies using different datasets and methods. These summaries offer valuable insights into current trends and successful applications in the literature.

Kazan and Karakoca (2019) used to classify categories with machine learning algorithms, product information from an e-commerce website was analyzed. Two different feature extraction techniques, TF-IDF and CountVectorizer, were compared during the data preprocessing phase, and six categories were classified using various classifiers (Random Forest, Decision Tree, Naive Bayes, Logistic Regression, SVM, ANN). According to the results, the SVM and MLP algorithms showed the highest performance with an accuracy rate of 97%. Yüce and Kabak (2021) applied machine learning algorithms to estimate production time in work centers related to four different processes in a manufacturing facility. The comparison of artificial neural networks, support vector regression, and gradient boosting algorithms revealed that the gradient boosting model achieved the highest success rate. The results demonstrated that selecting the right algorithm for production time estimation provides significant advantages in terms of cost and time.

Alnahhal et al. (2021) investigate the dynamic prediction of whether customer orders will arrive in the next delivery week using machine learning. Real data from December 2014 to August 2016 was used. Predictions using methods such as moving averages, simple linear regression, and logistic regression achieved an accuracy rate of 93%. The results are utilized to reduce waiting times at the consolidation center and lower transportation costs. (Erkmen et al., 2022) utilized the Support Vector Machine model with sequential and periodic look-back approaches to predict delivery times. Analysis with data obtained from Kaggle showed that using look-back approaches reduced prediction error by 59.12%. Khiari and Olaverri-Monreal (2020) applied various boosting algorithms to predict delivery times using seven months of data from a postal service company in Austria. Algorithms like Light Gradient Boosting and CatBoost outperformed other methods with high accuracy and efficiency. These approaches increased operational efficiency by ensuring accurate prediction of delivery times.

Lochbrunner and Witschel (2022) developed three different models combining machine learning models with human knowledge to predict delivery times using shipping data from a large retailer. Using the XGBoost regression algorithm and SHAP explanatory package, it was found that pure machine learning models performed better than human-machine combinations. However, both approaches had specific weaknesses and areas for improvement. (Rokoss et al., 2024) analyzed the data of two German manufacturing companies, using machine learning approaches to predict delivery times in small batch production companies. Predictions with machine learning models such as XGBoost could accurately predict delivery times early, effectively reducing manual efforts. These approaches provided significant results in enhancing the efficiency of the production process. Salari et al. (2022) applied tree-based models like quantile regression forests to predict delivery times and manage customer promises in online retail using JD.com data. The proposed methods increased prediction accuracy by over 40% compared to existing methods and boosted sales volume by 3.7% to 6.1%. This approach significantly improved customer satisfaction and operational efficiency.

Bruni et al. (2023) developed a machine learning-based optimization approach for last-mile delivery and third-party logistics services and tested it with real data from Italy. The proposed method provided high performance in a shorter time than existing heuristic methods and effectively optimized logistics processes. Chu et al. (2023) developed a data-driven approach combining machine learning and capacity-constrained vehicle routing optimization to improve the last-mile delivery performance of online food delivery platforms. Analyses using multi-source real data showed that the proposed method performed approximately 5% better than other methods. Sheng Liu (2021) developed a framework integrating travel time predictors with order assignment optimization to improve last-mile delivery performance using two months of data from a food delivery service provider in China. Analyses using machine learning and robust optimization tools enhanced the accuracy and efficiency of order assignment decisions. This method significantly improved the timely performance of last-mile delivery services. Gore et al. (2023) optimized digital marketing strategies in the food delivery business using ensemble learning methods supported by various algorithms. Decision trees, nearest neighbors, and Naive Bayes algorithms, along with ensemble learning methods such as Random Forest, Gradient Boosting, and XGBoost, were used. The results showed that these methods significantly improved the accuracy of marketing strategies, enhancing customer satisfaction.

Deshmukh et al. (2024) used data analysis and machine learning techniques to increase the delivery efficiency of electronic products on e-commerce platforms. He conducted an analysis with over 100,000 transaction data from January 2019 to December 2019, proposing route optimization and increasing logistics capacities during peak periods. Zaghloul et al. (2024) compared machine learning and deep learning methods to predict customer satisfaction in online retail using over 100,000 order data from a major retailer. The Random Forest model showed the best performance with a 92% accuracy rate and identified delivery time and order accuracy as the most influential factors on customer satisfaction. The summary of methods and key findings of the literature reviews is presented in Table 1.

In the literature, reviews on predicting delivery times in e-commerce logistics rely on small datasets. For example, Kazan and Karakoca (2019) and Khiari and Olaverri-Monreal (2020) used limited timeframes and small datasets in their analyses. While studies like those by Salari et al. (2022) and Deshmukh et al. (2024) have focused on larger datasets, such research remains in the minority. This study addresses these gaps by conducting a comprehensive analysis using large-scale Amazon delivery data. Unlike prior research, this approach incorporates broader timeframes and diverse logistics scenarios, aiming to contribute to more accurate predictions of delivery times and advancing the current state of e-commerce logistics research.

Table 1. Details of reviews

Paper	*Method*	*Key Findings*	*Dataset*
Kazan and Karakoca (2019)	Machine learning classification with TF-IDF & CountVectorizer	SVM and MLP achieved 97% accuracy	E-commerce product data
(Yüce and Kabak (2021)	ANN, SVM, Gradient Boosting	Gradient Boosting had the highest success rate	Manufacturing facility data
Alnahhal et al. (2021)	Dynamic prediction using machine learning	Logistic regression achieved 93% accuracy	Data from Dec 2014 to Aug 2016
Erkmen et al. (2022)	SVM with look-back approaches	Look-back approaches reduced error by 59.12%	Kaggle delivery data
Khiari and Olaverri-Monreal (2020)	Boosting algorithms for delivery time prediction	CatBoost outperformed others with high accuracy	7 months of postal service data
Lochbrunner and Witschel (2022)	XGBoost regression, SHAP explanation	ML models outperformed human-machine combos	Retailer shipping data
Rokoss et al. (2024)	XGBoost for small batch production	XGBoost accurately predicted delivery times	Data from 2 manufacturing companies
Salari et al. (2022)	Tree-based models for delivery time prediction	Prediction accuracy improved by over 40%	JD.com delivery data
Bruni et al. (2023)	ML-based optimization for last-mile delivery	High performance in a shorter time	Real data from Italy
Chu et al. (2023)	Data-driven vehicle routing optimization	Improved last-mile delivery by 5%	Multi-source real data
Sheng Liu (2021)	ML for travel time and order assignment	Enhanced order assignment accuracy	2 months of food delivery data
Gore et al. (2023)	Ensemble learning for marketing strategies	Improved marketing strategy accuracy	Digital marketing data
Deshmukh et al. (2024)	ML for delivery efficiency of electronic products	Increased delivery efficiency during peak periods	100,000 transaction data

3. PROPOSED MODELS

This section encompasses the dataset characteristics, the suggested method and model, the experimental setup, the obtained results and discussion.

3.1. Dataset

The dataset is provided as a comma-separated values (CSV) file containing Amazon's delivery data. This dataset offers a detailed overview of the company's last-mile logistics operations. Each row consists of delivery data from various cities, including information on order details, delivery agents, weather and traffic conditions, and delivery performance metrics, as outlined in Table 2. The dataset enables researchers and analysts to explore the factors influencing delivery efficiency, identify optimization opportunities, and examine the impact of various variables on the overall customer experience.

The dataset is utilized to classify delivery times, optimize delivery efficiency, and identify potential improvement areas aimed at enhancing customer satisfaction through the application of machine learning and ensemble learning methods. By employing machine learning algorithms and ensemble learning techniques, the relationships among various features within the dataset will be analyzed, and models with the highest accuracy rates will be selected to evaluate the performance of logistics operations. This approach contributes to the development of data-driven strategies to improve delivery efficiency and customer experience.

Machine learning and ensemble learning models are applied to the preprocessed dataset. Initially, the features related to each order delivery are considered. Subsequently, the processes of handling missing data and eliminating insignificant data with very few instances are carried out. Following this, feature extraction and the application of machine learning and ensemble learning models are performed. Feature extraction plays a critical role in transforming raw attributes into meaningful predictors for machine learning models. For instance, geospatial data (latitude and longitude of store and drop locations) is processed using the Haversine formula to calculate the actual distance between points. This transformation provides a single numerical feature representing the delivery distance, which directly correlates with delivery time and significantly improves model performance. Similarly, temporal attributes, such as 'Order_Date' and 'Order_Time,' are converted into timestamp values to facilitate numerical processing. Additionally, the time difference between 'Order_Time' and 'Pickup_Time' is calculated to represent delays in warehouse operations. These extracted features enhance the predictive capacity of the models, enabling more accurate delivery time classifications. Subsequently, various machine learning and ensemble learning methods are systematically applied to identify the most effective model for improving the efficiency of logistics processes. The data processing workflow for machine and ensemble learning is illustrated in Figure 1.

Table 2. Details of dataset

Feature Name	*Description*	*Value Range*
Order_ID	Unique identifier assigned to each order.	Unique values
Agent_Age	Age of the delivery agent.	Numerical values (15-50)
Agent_Rating	Rating assigned to the delivery agent based on performance.	Numerical values (0-5)
Store_Latitude	Latitude coordinate of the store location.	Numerical values (-30.90 - 30.91 degrees)
Store_Longitude	Longitude coordinate of the store location.	Numerical values (-88.37 - 88.43 degrees)
Drop_Latitude	Latitude coordinate of the delivery destination.	Numerical values (-30.90 - 30.91 degrees)
Drop_Longitude	Longitude coordinate of the delivery destination.	Numerical values (-88.37 - 88.43 degrees)
Order_Date	Date when the order was placed.	Date values (2022-02-11 - 2024-07-03)
Order_Time	Time when the order was placed.	Time values (00:00:00 – 23:55:00)
Pickup_Time	Time when the order was picked up from the store.	Time values (00:00:00 – 23:55:00)
Weather	Weather conditions during the delivery period.	Categorical values (e.g., clear, rainy, stormy)
Traffic	Traffic conditions encountered during the delivery.	Categorical values (e.g., light, moderate, heavy)
Vehicle	Type of vehicle used for the delivery.	Categorical values (e.g., bike, car, van)
Area	Geographic area or zone where the delivery took place.	Categorical values (e.g., metropolitan, urban, semi-urban, other)
Delivery Time	Total time taken to complete the delivery.	Numerical values (10 – 270 minutes)
Category	Classification of the delivered item.	Categorical values (e.g., clothing, electronics, sports, cosmetics, toys)

3.2. Preprocessing

In this study, machine learning and ensemble learning models are proposed using an Amazon delivery dataset. The dataset consists of 43,739 different delivery records and 15 features, containing the delivery data of Amazon's e-commerce system.

The data preprocessing phase involves six distinct steps: filling missing values, removing missing values, converting categorical data, extracting meaningful features, creating classes, and normalization. The preprocessing steps were chosen to address the specific characteristics of the dataset and enhance model performance. Missing values were imputed using the mean method to preserve the data's overall distribution. While other techniques such as median or mode imputation were considered, the mean method was deemed most appropriate given the low percentage of missing values (0.123%). Similarly, categorical variables were encoded using a combination of label encoding and one-hot encoding to ensure compatibility with machine learning algorithms. The data preprocessing phase involves six distinct steps:

1. Filling Missing Values: Missing values were filled using the mean method to prevent any bias in the model training. This technique was chosen because it preserves the overall distribution of the data, which is crucial when working with large-scale datasets. In the original dataset, there are 54 missing values for the “Agent_Rating” attribute. These missing cells are filled by calculating the mean of the other “Agent_Rating” values. Given the total number of records in the dataset, the ratio of missing values to the total data is 0.123%. Therefore, completing the missing values based on the mean has a minimal impact on the overall structure of the dataset.

2. Removing Missing Values: In the original dataset, some records have many cells corresponding to different attributes marked as “NaN”. This results in incomplete information for those records and can cause issues with the performance of machine learning models. Thus, such records are removed. Out of the total 43,739 records in the dataset, only 91 records contain “NaN” values, which constitute merely 0.208% of the total dataset. Due to the very low ratio of missing values, removing these records has a minimal impact on data integrity.

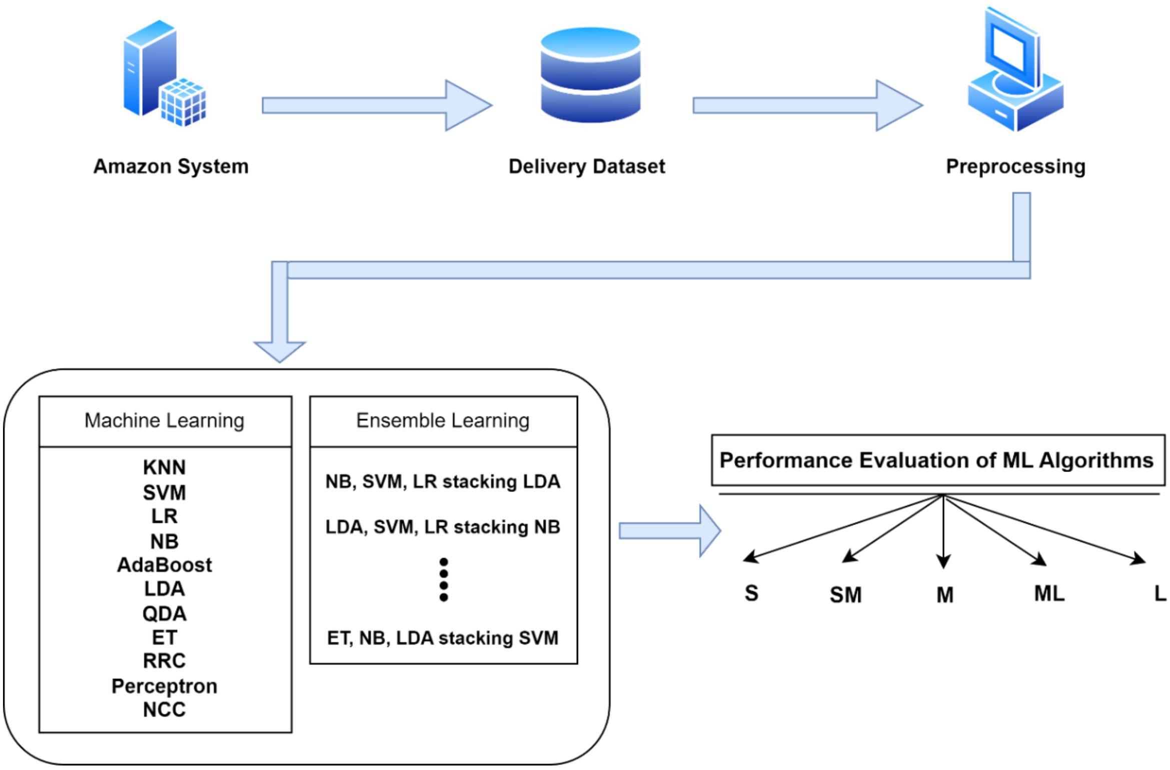

Figure 1. Data processing for machine and ensemble learning

3. Converting Categorical Data: Categorical data were converted into numerical representations using label encoding and one-hot encoding techniques. This conversion was necessary because most machine learning models work with numerical inputs, and categorical features need to be transformed into a format that can be interpreted by the model. The dataset contains categorical values for the attributes "Weather," "Traffic," "Area," "Vehicle," and "Category." These categorical values are converted into numerical representations. For example, the values high, jam, low, and medium in the "Traffic" column are represented by 1, 2, 3, and 4, respectively.

4. Extracting Meaningful Features: The attributes "Order_Date," "Order_Time," and "Pickup_Time" consist of date and time values. To express datetime values as numerical values, they are converted into timestamp values. A timestamp typically represents the number of seconds since January 1, 1970. This conversion is particularly useful in data analysis and machine learning models dealing with time data (Dyreson and Snodgrass 1993). For instance, for a record with "Order_Date" as 2022-03-19, "Order_Time" as 11:30:00, and "Pickup_Time" as 11:45:00, the combined "Order_Datetime" value represents March 19, 2022, at 11:30:00 and is converted into a timestamp value of 1,647,691,800 seconds. Similarly, the "Pickup_Datetime" value of March 19, 2022, at 11:45:00 is converted into a timestamp value of 1,647,692,700 seconds. These timestamp values facilitate the numerical processing and analysis of time data in data analysis and machine learning models. Similarly, distance data is obtained using the latitude and longitude values in the "Store_Latitude," "Store_Longitude," "Drop_Latitude," and "Drop_Longitude" columns. The Haversine formula is used to convert the latitude-longitude information of the store and drop locations into distance data. This formula gives the distance along a straight line passing through the center of the Earth between two points and represents the shortest distance between two points on the Earth's surface (Winarno, Hadikurniawati, and Rosso 2017). The values of longitude and latitude are determined using Equation 1. Subsequently, the intersection of the axis (c) is calculated as described in Equation 2. The final step in the Haversine method involves calculating the actual distance between two points using Equation 3.

$$a = \sin^2\left(\frac{\Delta\phi}{2}\right) + \cos(\phi_1)\cdot\cos(\phi_2)\cdot\sin^2\left(\frac{\Delta\lambda}{2}\right) \quad (1)$$

$$c = 2 \cdot \backslash\ \mathrm{atan}\ 2(\sqrt{a}, \sqrt{1-a}) \quad (2)$$

$$d = R \cdot c \quad (3)$$

5. Creating Classes: In classification algorithms, each feature must belong to a specific class. The Amazon delivery dataset's delivery times, which range from 10 to 270 minutes, are divided into five classes: Short (S), Short-Medium (SM), Medium (M), Medium-Long (ML), and Long (L). This division ensures that each class has equal width. Consequently, delivery times are classified as follows: 10-58 minutes (S), 59-106 minutes (SM), 107-154 minutes (M), 155-202 minutes (ML), and 203-270 minutes (L). The "Delivery_Class" column, created in this manner, is added to the dataset. The purpose of creating these classes is to enhance the performance of machine learning models and enable more precise predictions of delivery times. By using equal-width classes, the duration range represented by each class is balanced, thereby minimizing data imbalance during the model training process.

6. Normalization: Machine learning models tend to bias towards higher value data; hence, it is necessary to represent the data on a specific scale. Normalization is performed to ensure that each data point has the same scale and importance. In this study, the min-max normalization technique is chosen because it is simple, flexible, and intuitive. Min-max normalization scales the values of features (feature columns) in the dataset to the range [0, 1] (Patro and Sahu 2015). The new value of each data point is calculated according to Equation 4.

$$X_n = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (4)$$

After the preprocessing steps, the dataset is input into machine learning algorithms, and the results are calculated according to different machine learning metrics.

3.3. Details of Proposed Machine Learning and Ensemble Learning Models

The application of machine learning and ensemble learning methods on a dataset containing Amazon delivery information aims to classify delivery times, optimize delivery efficiency, and identify potential improvement areas to enhance customer satisfaction. The selected models (e.g., KNN, SVM, Logistic Regression) were chosen based on their well-documented performance in classification tasks involving structured data. For instance, SVM is known for handling high-dimensional data well, while Random Forest is effective in preventing overfitting. These models were chosen to cover a broad spectrum of machine learning techniques, ensuring that the best possible model for the dataset is identified. By employing machine learning algorithms and ensemble learning techniques, the relationships among various features within the dataset will be analyzed, and models with the highest accuracy will be selected to evaluate the performance of logistics operations. This approach will make significant contributions to the development of data-driven strategies for improving delivery efficiency and customer experience.

Using machine learning and ensemble learning algorithms on delivery data allows for more accurate and precise predictions of delivery times, contributing to optimized logistics efficiency and increased customer satisfaction. These methods predict potential delays and issues based on historical data, identify bottlenecks in operational processes, and enable proactive measures. The use of accuracy, precision, recall, and F-score as evaluation metrics ensures a comprehensive assessment of model performance. F-score, in particular, is useful in this context as it balances both precision and recall, which are critical in ensuring timely and accurate delivery predictions in logistics operations. Additionally, they support data-driven decision-making processes, aiding in more effective resource utilization and reducing logistics costs. Consequently, continuous improvement of delivery processes and the implementation of innovative solutions become possible.

In machine learning, models are developed using classification techniques such as K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Logistic Regression (LR), Naive Bayes (NB), AdaBoost, Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), ExtraTrees (ET), Ridge Regression Classifier (RRC), Perceptron, and Nearest Centroid Classifier (NCC). These models are trained to obtain results, categorizing data based on specific features and offering various advantages in different situations. KNN is effective for small datasets due to its simplicity and understandability (Guo et al., 2003: 988). SVM performs well with high-dimensional datasets and aims to find the best separating hyperplane (Wang and Hu, 2005). Logistic Regression provides fast and effective results, particularly in binary classification problems. Naive Bayes is a quick and computationally easy model under the assumption of independence. AdaBoost enhances accuracy by sequentially boosting weak learners. LDA separates data with linear combinations that provide maximum separation (Jelodar et al. 2019). QDA is effective when class boundaries are not linear (Ghojogh and Crowley 2019). ExtraTrees reduces the risk of overfitting by increasing model diversity (Ahmad, Reynolds, and Rezgui 2018). RRC prevents overfitting using regularization (He et al. 2014). Perceptron is quick and effective in simple linear separation problems (Gallant, 1990). NCC quickly classifies based on distance to each class's centroid (Sharma and Paliwal 2010). The selection of the most suitable model for specific data types and problems directly impacts the model's success. The performance of classification algorithms depends on various factors such as the quality of the training dataset, feature engineering, and model optimization techniques.

In machine learning, methods can be combined within a logical framework to create ensemble learning models. Bagging, stacking, and boosting form the three fundamental structures of ensemble learning. Firstly, in the bagging method, the dataset is usually divided into test and training groups in a 70/30 ratio. Specific numbers of bags are created by randomly and repeatedly sampling from the training data. Each bag is trained using well-known models. During decision-making, outputs are evaluated by averaging or voting. Similar to bagging, the boosting process also involves data splitting and random sampling. However, in boosting, each sample is independently trained and produces outputs like in bagging, giving each model an equal chance of success (Karakaya et al., 2022).

In the boosting process, three classifier sets are created simultaneously. Like bagging, the first and second classifiers are trained with various randomly selected segments of the dataset. The third classifier is trained on the data where the first and second classifiers fail. These three classifiers are then combined using the majority voting technique. On the other hand, the stacking method makes deci. P8sions based on the percentage of the feature area each classifier succeeds in. The outputs of the classifiers are combined with another classifier to make the final decision (Polikar, 2012: 8).

Ensemble learning using stacking is illustrated in Figure 2. Ensemble learning techniques such as stacking and bagging were chosen for their ability to combine the strengths of individual models. For example, stacking integrates diverse base models, capturing complementary patterns in the data. These techniques help in improving the robustness of predictions and reducing overfitting, which is particularly important when working with complex datasets like the Amazon delivery data. Compared to single classifiers such as SVM or Logistic Regression, ensemble methods show higher accuracy and resilience to overfitting in this study, as evidenced by their superior performance metrics. Four different base classifier examples are provided. Depending on the model design, more or fewer classifiers can be used. A new example is evaluated by each classifier for classification. The results of each classifier are then evaluated by a new meta-classifier. Based on the meta-classifier's result, the example data is labeled with a class tag (Sagi and Rokach 2018). The preference for using the stacking method in the proposed model is due to its ability to combine the strengths of different machine learning models, enhancing overall performance. Using stacking to classify delivery times based on the Amazon delivery dataset allows each model to capture different features, resulting in more precise and accurate predictions. Additionally, the stacking method increases model diversity, reducing the risk of overfitting and enhancing generalization capability. This approach improves the classification of delivery times and makes logistics operations more efficient.

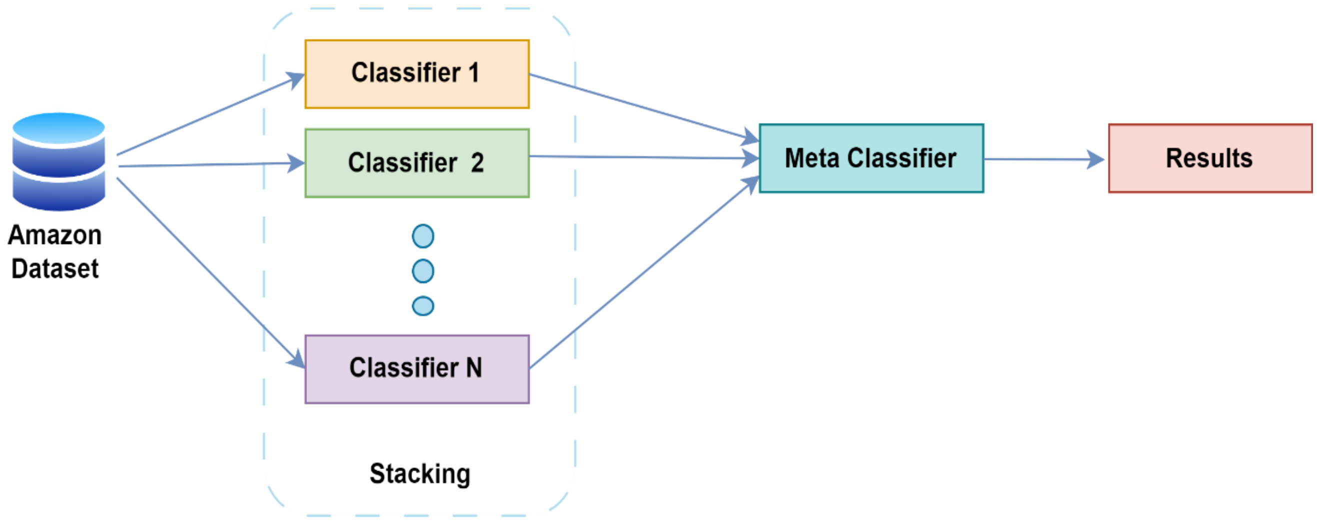

Figure 2. Stacking process in the ensemble learning

One of the ensemble learning methods is the voting classifier. The structure of a voting classifier consists of a machine learning model that evaluates predictions both hard and soft. In hard voting, the prediction with the most votes wins. In soft voting, the probabilities produced by each machine learning model are considered, and the class with the highest weighted average probability wins.

3.4. Experimental Design

The experimental studies of the proposed method were conducted on a computer with an AMD Ryzen 7 4800H processor running at 2.9 GHz, 16 GB RAM, and Windows 10 operating system, using Python 3.x. Stacking-based ensemble learning models, where machine and ensemble learning models such as KNN, SVM, LR, NB, AdaBoost, LDA, QDA, ET, RRC, Perceptron, and NCC serve as base and meta classifiers, were trained and tested on the Amazon delivery dataset. As a result of these processes, the models with the highest performance were identified as ensemble learning models. Each model was compared using the parameters of accuracy, precision, recall, and F-score (Reddy and Karthikeyan 2022). These metrics are obtained from the confusion matrix of the model's output, which includes four states: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) (Vujović 2021). The first metric evaluated using these states is accuracy, which indicates the ratio of correct predictions to the total number of predictions made. The accuracy formula is provided in Equation 5.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{5}$$

Precision, which is the ratio of correctly predicted positive results to all predicted positive results, is given by Equation 6.

$$Precision = \frac{TP}{TP+FP} \tag{6}$$

Recall, defined as the ratio of correctly predicted positive results to all actual positive results, is shown in Equation 7.

$$Recall = \frac{TP}{TP+FN} \tag{7}$$

The F-score, representing the weighted harmonic mean of precision and recall, is calculated using Equation 8.

$$Fscore = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \tag{8}$$

4. RESULTS and DISCUSSION

In this study, various machine learning and ensemble learning models are evaluated for classifying delivery statuses using the Amazon delivery dataset. Performance metrics such as precision, recall, accuracy, and F-score are presented in Table 3 for each machine learning model and in Table 4 for each ensemble learning model. The results indicate that ensemble methods generally outperform individual classifiers.

Among the machine learning models, ET demonstrated superior performance, achieving the highest accuracy (0.978389) and F-score (0.978315), effectively capturing the delivery status. LDA also proved to be a robust choice with high accuracy (0.974189) and precision (0.974753). SVM performed well among individual classifiers, with an accuracy of 0.971592 and a high F-score of 0.971414. LR and NB also demonstrated good performance, with accuracies of 0.960825 and 0.962199, respectively, highlighting their effectiveness for this classification problem.

In contrast, models such as KNN and RRC exhibited lower performance metrics, revealing limitations in handling the complexity of the dataset. Perceptron and NCC also had relatively low accuracy and F-scores, indicating that these models are not well-suited for this particular application. The superior performance of the ET model can be attributed to its ability to handle large and complex datasets by reducing the risk of overfitting through randomized tree ensembles. SVM's effectiveness, on the other hand, stems from its capacity to handle high-dimensional data and find optimal hyperplanes for classification. In contrast, models like KNN and NCC, which rely heavily on proximity measures, struggle with the dataset's complexity and variability, leading to lower performance metrics.

Tablo 3. Machine learning model results

Model	*Precision*	*Recall*	*Accuracy*	*F-score*
KNN	0.691618	0.687743	0.687743	0.687265
SVM	0.971792	0.971592	0.971592	0.971414
LR	0.961722	0.960825	0.960825	0.960278
NB	0.962634	0.962199	0.962199	0.962118
AdaBoost	0.679882	0.803436	0.803436	0.727570
LDA	0.974753	0.974189	0.974189	0.973957
QDA	0.955301	0.954486	0.954486	0.954418
ET	0.978672	0.978389	0.978389	0.978315
RRC	0.689599	0.633906	0.633906	0.576764
Perceptron	0.714537	0.616953	0.616953	0.603055
NCC	0.523986	0.517297	0.517297	0.512587

The results demonstrate that ensemble learning approaches yield successful performance. When using NB, SVM, and LR as base models, and ET as the meta model, the highest accuracy (0.994196) and F-score (0.994201) were achieved. Similarly, high performance was observed when using LDA, LR, and ET as base models, and SVM as the meta model (accuracy: 0.994425, F-score: 0.994422). Notably, the highest performance (accuracy: 0.998931, F-score: 0.998930) was achieved with SVM, NB, and LDA as base models, and ET as the meta model. This result indicates that the ET model has a strong classification capacity when combined with other models. Conversely, some combinations showed relatively lower performance. For instance, when ET, SVM, and LDA were used as base models, and NB was selected as the meta model, both accuracy and F-score were recorded at 0.982971. This suggests that certain meta models may not perform optimally with specific combinations of base models. ET-based meta models and SVM combinations, in particular, stand out in enhancing classification accuracy.

Tablo 4. Ensemble learning (stacking) model results

Base Model - Meta Model	*Precision*	*Recall*	*Accuracy*	*F-Score*
Base Model (NB, SVM, LR) - Meta Model(LDA)	0.972463	0.972279	0.972279	0.972176
Base Model (NB, SVM, LR) - Meta Model(QDA)	0.966922	0.963650	0.963650	0.964250
Base Model (NB, SVM, LR) - Meta Model(ET)	0.994230	0.994196	0.994196	0.994201
Base Model (LDA, SVM, LR) - Meta Model(NB)	0.974985	0.973807	0.973807	0.973940
Base Model (QDA, SVM, ET) - Meta Model(LR)	0.990145	0.990149	0.990149	0.990145
Base Model (LDA, LR, ET) - Meta Model(SVM)	0.994425	0.994425	0.994425	0.994422
Base Model (SVM, NB, LDA) - Meta Model(ET)	0.998932	0.998931	0.998931	0.998930
Base Model (ET, NB, LDA) - Meta Model(SVM)	0.995343	0.995342	0.995342	0.995340
Base Model (ET, SVM, LDA) - Meta Model(NB)	0.983242	0.982971	0.982971	0.982985
Base Model (ET, SVM, NB) - Meta Model(LDA)	0.981309	0.981214	0.981214	0.981180

According to Tables 3 and 4, the ET model achieved the highest accuracy (0.978389) and F-score (0.978315). SVM and LDA also demonstrated high performance, with accuracy values of 0.971592 and 0.974189, respectively. Conversely, ensemble learning models, particularly when using SVM, NB, and LDA as base models and ET as the meta model, exhibited superior performance with the highest accuracy (0.998931) and F-score (0.998930). The practical significance of these findings lies in the ability of the top-performing models to predict delivery times more accurately than traditional approaches. This allows e-commerce companies to enhance operational efficiency by better managing delivery schedules and minimizing delays. Furthermore, the ability to predict delivery times with such precision offers companies a competitive edge, as faster and more reliable delivery services directly impact customer satisfaction. These models can be applied in real-time logistics operations, enabling proactive responses to potential delays, improving route planning, and ultimately optimizing the entire delivery process. This indicates that ensemble learning approaches are more effective than individual machine learning models. Ensemble learning provides better performance due to the generalization capability achieved by combining various models. In this context, ensemble learning models, especially those with ET-based meta models and SVM combinations, are significantly superior in enhancing classification accuracy. These results underscore the necessity of employing ensemble learning techniques for complex datasets.

Tablo 5. Sensitivity analysis data based on train/test split

Model	*Split*	*Precision*	*Recall*	*Accuracy*	*F-score*
ET	60/40	0.978448	0.978179	0.978179	0.978079
	70/30	0.978672	0.978389	0.978389	0.978315
	80/20	0.979297	0.979038	0.979038	0.978971
	90/10	0.978436	0.978236	0.978236	0.978180
Base Model (SVM, NB, LDA) - Meta Model (ET)	60/40	0.995134	0.995132	0.995132	0.995132
	70/30	0.998932	0.998931	0.998931	0.998930
	80/20	0.993364	0.993356	0.993356	0.993355
	90/10	0.994969	0.994960	0.994960	0.994961

The results presented in Table 5 illustrate how the performance metrics of the models vary with different split ratios. The experimental studies involve dividing the dataset into training and testing subsets at various split ratios to evaluate the sensitivity of model performance. This study employed a sensitivity analysis approach by dividing the dataset into training and testing subsets at multiple split ratios (60/40, 70/30, 80/20, and 90/10). This method allowed for the evaluation of model performance across different data distributions, providing insights into the robustness and generalizability of the proposed models. The top-performing models, particularly the ensemble learning approach using SVM, NB, LDA, and ET, offer significant practical usability for e-commerce companies. These models can be integrated into logistics management systems to predict delivery times with high accuracy, enabling more precise scheduling and efficient resource allocation. By identifying potential delays and optimizing delivery routes, these models contribute to reducing operational costs and enhancing customer satisfaction. The ET model consistently achieved high accuracy and F-score values across all split ratios. Specifically, the highest accuracy (0.979038) and F-score (0.978971) were attained with the 80/20 split ratio. The ET model demonstrated similarly high performance with other split ratios, indicating better generalization when a larger portion of the dataset is used for training. The ensemble learning model combining Base models (SVM, NB, LDA) and the Meta model (ET) showed the best performance across all split ratios. Notably, the highest accuracy (0.998931) and F-score (0.998930) were achieved with the 70/30 split ratio. These results indicate that ensemble learning models maintain high performance regardless of the train/test split ratio. In conclusion, while train/test split ratios can impact the performance of machine learning models, ensemble learning models demonstrate more stable performance. This underscores the ability of ensemble learning techniques to provide consistent results across different portions of the dataset.

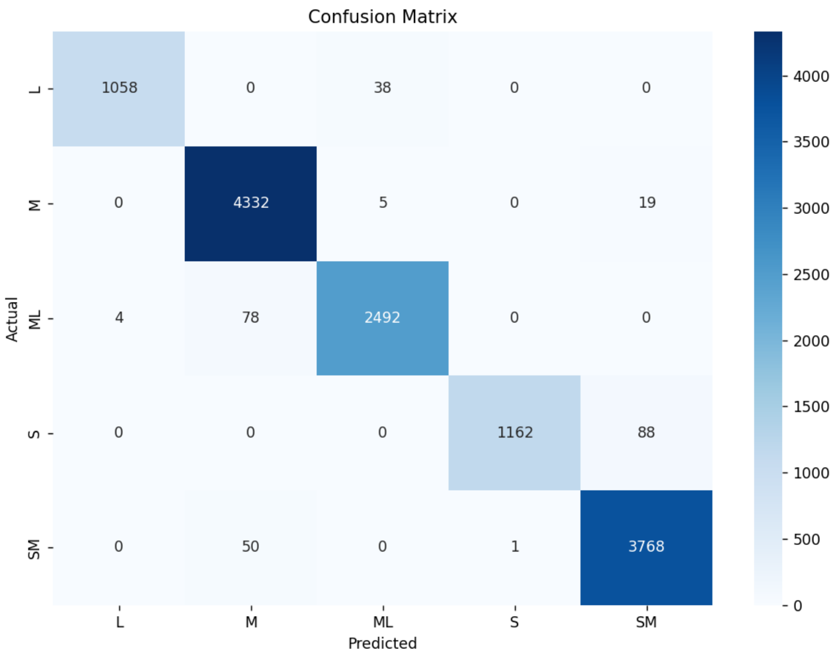

Figure 3. Confusion matrix for ET

Figure 3 presents the confusion matrix, illustrating the performance of the ET model in classifying delivery times. The delivery times are categorized into five classes: S, SM, M, ML, and L. Overall, the model exhibits a high classification accuracy.

- In the S class, there were 1162 correct classifications, with 88 instances misclassified as SM.
- In the SM class, there were 3768 correct classifications, with 50 instances misclassified as M and 1 as S.
- In the M class, there were 4332 correct classifications, with 5 instances misclassified as ML and 19 as SM.
- In the ML class, there were 2492 correct classifications, with 4 instances misclassified as L and 78 as M.
- In the L class, there were 1058 correct classifications, with 38 instances misclassified as ML.

These results indicate that the model generally distinguishes delivery times successfully, although some confusion exists, particularly between the M and ML classes. This confusion might stem from the indistinct boundaries between these classes. Overall, the ET model is effective in accurately classifying delivery times.

Figure 4 presents the confusion matrix for the ensemble learning model using SVM, NB, and LDA as Base Models and ET as the Meta Model, illustrating its performance in classifying delivery times.

- In the S class, 1243 instances were correctly classified, with 7 instances misclassified as SM.
- In the SM class, 3818 instances were correctly classified, with only 1 instance misclassified as S.
- In the M class, 4355 instances were correctly classified, with only 1 instance misclassified as ML.
- In the ML class, 2570 instances were correctly classified, with 4 instances misclassified as M.

- In the L class, 1093 instances were correctly classified, with only 3 instances misclassified as ML.

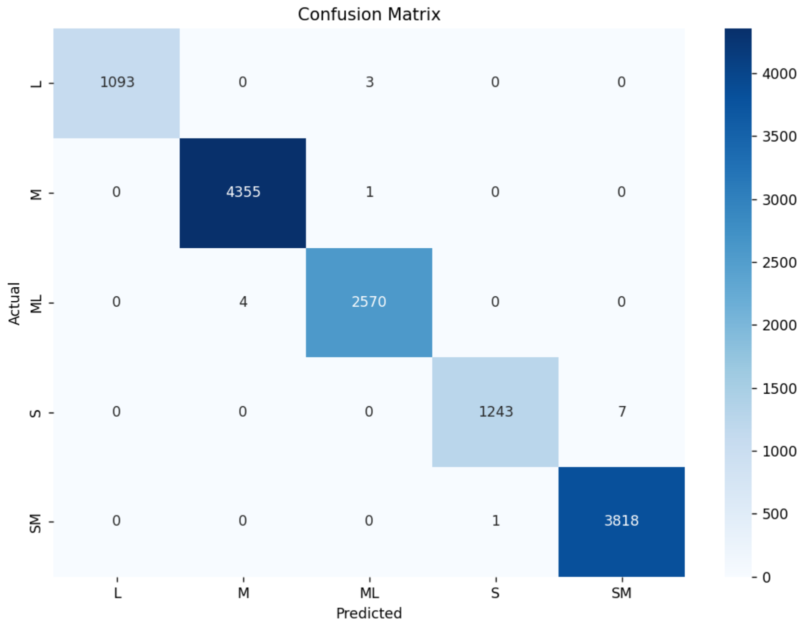

Figure 4. Confusion matrix for Base Model (SVM, NB, LDA) - Meta Model (ET)

These results indicate that the ensemble learning model is highly effective in accurately classifying delivery times, demonstrating superior performance. The minimal misclassifications, particularly between the M and ML classes, highlight the model's ability to effectively distinguish delivery times. Overall, the model exhibits a high level of accuracy in delivery time classification.

The results of this study highlight the significant potential of machine learning and ensemble learning models in transforming logistics operations, particularly in e-commerce. The high accuracy and reliability demonstrated by the ensemble learning models, such as the stacking method combining SVM, NB, and ET, offer robust solutions for predicting delivery times. These predictions are critical for optimizing key logistics functions, including route planning, resource allocation, and last-mile delivery. For instance, the ability to accurately forecast delivery times enables logistics companies to minimize delays, reduce fuel consumption, and allocate resources more effectively, thereby improving overall operational efficiency.

One of the most practical implications of these findings is the enhancement of customer satisfaction. Timely and reliable delivery is a cornerstone of customer loyalty in the competitive e-commerce market. By leveraging the predictive power of ensemble learning models, logistics companies can proactively identify potential delays and take corrective actions, such as rerouting deliveries or deploying additional resources. This proactive approach not only ensures timely deliveries but also fosters trust and reliability, which are crucial for sustaining customer relationships in the long term.

Beyond immediate operational benefits, these results also contribute to the broader logistics field by demonstrating the scalability and adaptability of ensemble learning methods for large-scale, dynamic datasets. Unlike traditional forecasting models, which often struggle with the complexities of modern logistics, the proposed models handle diverse variables such as traffic, weather, and geospatial data with high precision. Real-world applications could include integrating these models into logistics management systems for real-time decision-making. For example, warehouse operations can utilize these predictions to streamline inventory flow and optimize loading processes, while last-mile delivery teams can use them to enhance delivery route accuracy and reduce delivery windows.

Overall, the study underscores the transformative potential of machine learning and ensemble learning models in addressing logistical challenges. By improving prediction accuracy and operational efficiency, these models not only offer a competitive edge for e-commerce platforms but also pave the way for data-driven innovations in logistics and supply chain management.

5. CONCLUSION

In this study, we evaluated the performance of various machine learning and ensemble learning models in classifying delivery times using the Amazon delivery dataset. The results demonstrate that ensemble learning methods outperform individual machine learning models. Notably, the ensemble learning model using SVM, NB, and LDA as Base Models and ET as the Meta Model achieved the highest accuracy and F-score values across all split ratios. These findings indicate that ensemble learning approaches provide more consistent and superior performance on complex datasets. In practice, the application of top-performing models has the potential to revolutionize e-commerce logistics by providing highly accurate delivery time predictions. These models offer solutions that can be implemented in operational systems to improve customer satisfaction, optimize delivery routes, and reduce costs, making them highly valuable tools for modern logistics management.

Data preprocessing steps included filling and removing missing values, converting categorical data, extracting meaningful features, creating classes, and normalizing the dataset to make it suitable for machine learning and ensemble learning algorithms. The careful and accurate execution of these steps positively impacted the models' performance. Additionally, performance metrics such as precision, recall, accuracy, and F-score were effectively utilized to evaluate the models' accuracy and classification success. This study contributes to the field by demonstrating the effectiveness of ensemble learning methods in improving the prediction accuracy of e-commerce delivery times, a relatively underexplored area in large-scale logistics datasets. Unlike previous studies that primarily focused on smaller datasets, this research addresses the scalability of machine learning models, offering a more robust solution for real-world logistics management.

In conclusion, our study demonstrates that applying machine learning and ensemble learning models to Amazon delivery data allows for more accurate and precise prediction of delivery times. This contributes to optimizing logistics efficiency and enhancing customer satisfaction. The study aimed to answer two key research questions: (1) How can machine learning and ensemble learning models improve the accuracy of delivery time predictions? (2) Which model performs best across various logistics scenarios? (3) Which is the most effective model when the performance of methods is systematically compared with the aim of improving the efficiency of logistics processes? The results clearly show that ensemble learning models, particularly those involving ET, SVM, and NB, significantly enhance prediction accuracy. Additionally, the evaluation of different models underscores the superiority of ensemble methods in handling the complexities of large-scale logistics data, further validating their practical use in improving e-commerce delivery operations.

Despite the promising results, the study has certain limitations. The dataset used, although large, is confined to Amazon's delivery data, which may limit the generalizability of the findings to other logistics operations. Future studies could explore the application of these models across diverse datasets from different industries. Additionally, integrating real-time data and optimizing algorithms for specific logistical challenges, such as route optimization and vehicle management, could further improve model performance.

Future work has the potential to improve model performance by using expanded and diversified datasets. By exploring combinations of different machine learning and ensemble learning algorithms, innovative approaches that provide higher accuracy and efficiency in logistics operations can be developed. Applying these approaches to other logistics and supply chain processes could significantly enhance operational efficiency. Such data-driven strategies will continue to play a critical role in supply chain management practices, and further development of these methods could lead to significant innovations in the industry.

Conflict of Interest
No potential conflict of interest was declared by the author.

Funding
Any specific grant has not been received from funding agencies in the public, commercial, or not-for-profit sectors.

Compliance with Ethical Standards
It was declared by the author that the tools and methods used in the study do not require the permission of the Ethics Committee.

Ethical Statement
It was declared by the author that scientific and ethical principles have been followed in this study and all the sources used have been properly cited.

REFERENCES

Ahmad, M.W., Reynolds, J. and Rezgui, Y. (2018). "Predictive Modelling for Solar Thermal Energy Systems: A Comparison of Support Vector Regression, Random Forest, Extra Trees and Regression Trees", *Journal of Cleaner Production,* 203, 810-821. https://doi.org/10.1016/j.jclepro.2018.08.207

Alnahhal, M., Ahrens, D. and Salah, B. (2021). "Dynamic Lead-Time Forecasting Using Machine Learning in a Make-to-Order Supply Chain", *Applied Sciences*, 11(21), 10105. https://doi.org/10.3390/app112110105

Bruni, M.E., Fadda, E., Fedorov, S. and Perboli, G. (2023). "A Machine Learning Optimization Approach for Last-Mile Delivery and Third-Party Logistics", *Computers & Operations Research,* 157, 106262. https://doi.org/10.1016/j.cor.2023.106262

Chu, H., Zhang, W., Bai, P. and Chen, Y. (2023). "Data-Driven Optimization for Last-Mile Delivery", *Complex and Intelligent Systems,* 9(3), 2271-2284. https://doi.org/10.1007/s40747-021-00293-1

Deshmukh, Y., Patil, J., Pawar, P., Pardeshi, P. and Patil, H. (2024). "E-Commerce Product Delivery Analysis", *IRE Journals*, 7(12), 177-181.

Dyreson, C.E. and Snodgrass, R.T. (1993). "Timestamp Semantics and Representation", *Information Systems* 18(3), 143-166. https://doi.org/10.1016/0306-4379(93)90034-X

Erkmen, O.E., Nigiz, E., Z. Sarı, Z.D., Arlı, H.Ş. and Akay, M.F. (2022). "Delivery Time Prediction Using Support Vector Machine Combined with Look-Back Approach", *International Joint Conference on Engineering, Science and Artificial Intelligence-IJCESAI 2022*, 33-38.

Eskandaripour, H. and Boldsaikhan, E. (2023). "Last-Mile Drone Delivery: Past, Present, and Future", *Drones,* 7(2), 77. https://doi.org/10.3390/drones7020077

Gallant, S.I. (1990). "Perceptron-Based Learning Algorithms", *IEEE Transactions on Neural Networks*, 1(2), 179-191.

Ghojogh, B., and Crowley, M. (2019). "Linear and Quadratic Discriminant Analysis: Tutorial", arXiv:1906.02590. https://doi.org/10.48550/arXiv.1906.02590

Gore, S., Mishra, P.K. and Gore, S. (2023). "Improvisation of Food Delivery Business by Leveraging Ensemble Learning with Various Algorithms", *International Conference on Self Sustainable Artificial Intelligence Systems, ICSSAS 2023*, 221-229. https://doi.org/10.1109/ICSSAS57918.2023.10331669

Guo, G., Wang, H., Bell, D., Bi, Y. and Greer, K. (2003). "KNN Model-Based Approach in Classification", *On The Move to Meaningful Internet Systems 2003: CoopIS, DOA, and ODBASE. OTM 2003. Lecture Notes in Computer Science*, (Editors: R. Meersman, Z. Tari, D.C. Schmidt), 2888, Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-540-39964-3_62

He, J., Ding, L., Jiang, L., and Ma, L. (2014). "Kernel Ridge Regression Classification", *Proceedings of the International Joint Conference on Neural Networks,* 2263-2267. https://doi.org/10.1109/IJCNN.2014.6889396

Jelodar, H., Wang, Y., Yuan, C., Feng, X., Jiang, X., Li, Y. and Zhao, L. (2019). "Latent Dirichlet Allocation (LDA) and Topic Modeling: Models, Applications, a Survey", *Multimedia Tools and Applications,* 78(11), 15169-15211. https://doi.org/10.1007/s11042-018-6894-4

Karakaya, A., Ulu, A. and Akleylek, S. (2022a). "GOALALERT: A Novel Real-Time Technical Team Alert Approach Using Machine Learning on an IoT-Based System in Sports", *Microprocessors and Microsystems,* 93, 104606. https://doi.org/10.1016/j.micpro.2022.104606

Kazan, S. and Karakoca, H. (2019). "Makine Öğrenmesi İle Ürün Kategorisi Sınıflandırma", *Sakarya University Journal of Computer and Information Sciences,* 2(1), 18-27. https://doi.org/10.35377/saucis.02.01.523139

Khiari, J., and Olaverri-Monreal, C. (2020). "Boosting Algorithms for Delivery Time Prediction in Transportation Logistics", *IEEE International Conference on Data Mining Workshops, ICDMW 2020*, 251-258. https://doi.org/10.1109/ICDMW51313.2020.00043

Lochbrunner, M., and Witschel, H.F. (2022). "Combining Machine Learning with Human Knowledge for Delivery Time Estimations", *CEUR Workshop Proceedings,* 3121.

Patro, S. and Sahu, K.K. (2015). "Normalization: A Preprocessing Stage." ArXiv Preprint ArXiv:1503.06462.

Polikar, R. (2012). "Ensemble Learning", *Ensemble Machine Learning: Methods and Applications*, (Editors: C. Zhang and Y. Ma), 1-34, Springer, New York.

Reddy, B.H., and Karthikeyan, P. R. (2022). "Classification of Fire and Smoke Images Using Decision Tree Algorithm in Comparison with Logistic Regression to Measure Accuracy, Precision, Recall, F-Score." *14th International Conference on Mathematics, Actuarial Science, Computer Science and Statistics (MACS)*. 1-5, IEEE.

Rokoss, A., Syberg, M., Tomidei, L., Hülsing, C., Deuse, J. and Schmidt, M. (2024). "Case Study on Delivery Time Determination Using a Machine Learning Approach in Small Batch Production Companies", *Journal of Intelligent Manufacturing,* 35, 3937-3958. https://doi.org/10.1007/s10845-023-02290-2

Sagi, O., and Rokach, L. (2018). “Ensemble Learning: A Survey”, *WIRES Data Mining and Knowledge Discovery,* 8(4), 1-18. https://doi.org/10.1002/widm.1249

Salari, N., Liu, S. and Max Shen, Z-J. (2022). “Real-Time Delivery Time Forecasting and Promising in Online Retailing: When Will Your Package Arrive?”, *Manufacturing and Service Operations Management,* 24(3), 1421-1436. https://doi.org/10.1287/msom.2022.1081

Sharma, A., and Paliwal, K.K. (2010). “Improved Nearest Centroid Classifier with Shrunken Distance Measure for Null LDA Method on Cancer Classification Problem”, *Electronics Letters,* 46(18), 1251-1252. https://doi.org/10.1049/el.2010.1927

Sheng L., He, L., and Max Shen, Z-J. (2021). “On-Time Last-Mile Delivery: Order Assignment with Travel-Time Predictors”, *Management Science,* 67(7), 4095-4119. https://doi.org/10.1287/mnsc.2020.3741

Tsang, Y.P., Wu, C-H., Lam, H.Y., Choy, K.L. and Ho, G.T.S. (2021). “Integrating Internet of Things and Multi-Temperature Delivery Planning for Perishable Food E-Commerce Logistics: A Model and Application”, *International Journal of Production Research,* 59(5), 1534-1556.

Tsolaki, K., Vafeiadis, T., Nizamis, A., Ioannidis, D. and Tzovaras, D. (2023). “Utilizing Machine Learning on Freight Transportation and Logistics Applications: A Review”, *ICT Express,* 9(3), 284-295.

Wang, H. and Hu, D. (2005). “Comparison of SVM and LS-SVM for Regression”, *2005 International Conference on Neural Networks and Brain*, 279-283. https://doi.org/10.1109/ICNNB.2005.1614615

Winarno, E., Hadikurniawati, W. And Rosso, R.N. (2017). “Location Based Service for Presence System Using Haversine Method”, *2017 International Conference on Innovative and Creative Information Technology (ICITech)*, Salatiga, Indonesia, 1-4. https://doi.org/10.1109/INNOCIT.2017.8319153

Yüce T. and Kabak M. (2021). “Makine Öğrenmesi Algoritmaları Ile Detay Üretim Alanları İçin İş Merkezi Kırılımında Üretim Süresi Tahminleme”, *Erciyes Üniversitesi Fen Bilimleri Enstitüsü Fen Bilimleri Dergisi*,37(1), 47-60.

Zaghloul, M., Barakat, S. and Rezk, A. (2024). “Predicting E-Commerce Customer Satisfaction: Traditional Machine Learning vs. Deep Learning Approaches”, *Journal of Retailing and Consumer Services*, 79, 103865. https://doi.org/10.1016/j.jretconser.2024.103865

Željko, V. (2021). “Classification Model Evaluation Metrics”, *International Journal of Advanced Computer Science and Applications,* 12(6), 599-606. https://doi.org/10.14569/IJACSA.2021.0120670

VERİMLİLİK DERGİSİ
JOURNAL OF PRODUCTIVITY

Efficiency Analysis of Turkish Container Ports: SFA or DEA?

İsmail Yenilmez[1]

ABSTRACT

Purpose: The study compares the efficiency of Turkish container ports using Stochastic Frontier Analysis and Data Envelopment Analysis. It aims to provide comparative insights for enhancing ports' operational performance. Capacity utilization and operational performance were analyzed in detail through ratio analysis.

Methodology: Two efficiency measurement techniques were employed: SFA evaluates efficiency by accounting for random errors and external factors, while DEA assesses relative efficiency by comparing ports to the best performers. Ratio analysis was used to evaluate capacity utilization through current handling capacity and annual growth rates.

Findings: Significant differences were observed between SFA and DEA results. Ports like MIP MERSİN and EVYAP demonstrated high efficiency in both methods, while discrepancies were detected in ports like MARDAŞ and ÇELEBİ BANDIRMA. SFA better captures external factors and operational challenges, whereas DEA emphasizes relative efficiency. For instance, MARDAŞ exhibited rapid growth in handling volume but low operational efficiency. Ratio analysis showed varying capacity utilization levels, with some ports operating near full capacity, while others, like AKÇANSA, operate at low capacity and need operational improvements.

Originality: The study provides a holistic view of port efficiency by integrating SFA, DEA, and ratio analysis. It not only measures comparative efficiency but also examines ports' capacity utilization. Differences in efficiency measures were discussed, with SFA offering valuable insights into strategic improvements by effectively reflecting operational challenges and external factors.

Keywords*:* Capacity Utilization, Operational Performance, Ratio Analysis, Logistics Efficiency.

JEL Codes: C44, C67, R41.

Türk Konteyner Limanlarının Etikinlik Analizi: SFA mı DEA mı?

ÖZET

Amaç: Stokastik Sınır Analizi ve Veri Zarflama Analizi yöntemleriyle Türk konteyner limanlarının verimliliği karşılaştırılmıştır. Çalışma, limanların operasyonel performansını artırmaya yönelik karşılaştırmalı bulgular sunmayı amaçlar. Oran analizi ile limanların kapasite kullanımı ve operasyonel performansları detaylı incelenmiştir.

Metodoloji: İki verimlilik ölçüm tekniği kullanılmıştır: SFA, rastgele hatalar ve dışsal faktörleri dikkate alarak verimliliği değerlendirirken; DEA, limanları en iyi performans gösterenlerle karşılaştırarak göreli verimliliği ölçmektedir. Oran analizi, mevcut elleçleme kapasitesi ve yıllık büyüme oranlarıyla kapasite kullanımını değerlendirmek için kullanıldı.

Bulgular: SFA ve DEA sonuçları arasında önemli farklılıklar gözlenmiştir. MIP MERSİN ve EVYAP gibi limanlar her iki yöntemde de yüksek verimlilik gösterirken, MARDAŞ ve ÇELEBİ BANDIRMA limanlarında yöntemler arasında farklar tespit edilmiştir. SFA'nın dışsal faktörleri ve operasyonel zorlukları daha iyi yakaladığı, DEA'nın ise göreli verimliliği öne çıkardığı görülmüştür. Özellikle MARDAŞ limanı, hızlı elleçleme büyümesine rağmen düşük operasyonel verimlilik sergilemektedir. Oran analizi, limanların kapasitelerini ne kadar verimli kullandığını ortaya koyarak, bazı limanların tam kapasiteye yakın çalışırken, AKÇANSA gibi limanların düşük kapasite ile çalıştığını göstermiştir.

Özgünlük: Çalışma, SFA ve DEA'yı oran analizi ile inceleyerek limanların verimliliğine bütünsel bir bakış sunmaktadır. Böylece sadece verimlilik karşılaştırmalı ölçülmemiş, aynı zamanda limanların kapasite kullanımları ele alınmıştır. SFA'nın, dışsal faktörleri etkin şekilde dikkate alarak operasyonel performansı yansıtması, stratejik iyileştirmeler için değerli bilgiler sunmaktadır.

Anahtar Kelimeler*:* Kapasite Kullanımı, Operasyonel Performans, Oran Analizi, Lojistik Verimliliği.

JEL Kodları: C44, C67, R41.

---

[1] Eskişehir Technical University, Faculty of Science, Department of Statistics, Eskişehir, Türkiye

Corresponding Author: İsmail Yenilmez, ismailyenilmez@eskisehir.edu.tr

DOI: 10.51551/verimlilik.1522007
Research Article | Submitted: 24.07.2024 | Accepted: 03.10.2024
Cite: Yenilmez, İ. (2025). "Efficiency Analysis of Turkish Container Ports: SFA or DEA?", *Verimlilik Dergisi,* Productivity for Logistics (SI), 105-118.

1. INTRODUCTION

Container ports are integral to the global supply chain, facilitating the movement of goods across international borders. In Türkiye, container ports serve as vital roles for trade between Europe and Asia. Evaluating the efficiency of these ports is essential for optimizing their performance and enhancing their competitive edge, particularly as global trade continues to evolve rapidly. Efficient port operations result in faster cargo handling, reduced vessel turnaround times, and lower operational costs, all of which strengthen competitiveness in the global market. By minimizing delays and maximizing throughput, efficient ports enable smoother supply chain operations, reducing the likelihood of bottlenecks and ensuring timely delivery of goods. This reliability not only strengthens trade relationships but also attracts more business, contributing to both national and regional economic growth. Specifically, efficient ports boost exports, support industrial sectors that rely on timely shipments, and create employment opportunities in logistics and related industries. In contrast, inefficient port operations can lead to increased costs, trade delays, and supply chain disruptions, negatively impacting economic growth and trade competitiveness (Cullinane et al., 2002; Talley, 2006; Panayides and Song, 2009).

Inefficiencies in supply chains, production processes, and logistics systems can lead to significant negative consequences in economic and trade environments. A primary effect is the lengthening of lead times, which refers to the period between the initiation of an order and its delivery. Prolonged lead times delay product availability in the market, resulting in disruptions that frustrate both consumers and businesses (Christopher, 2016, p. 4). Additionally, inefficiencies often lead to inventory buildup, as companies tend to overproduce or hold excess stock to mitigate uncertainties. This not only ties up capital but also increases storage and handling costs, making the entire supply chain less responsive and more expensive to operate (Slack and Brandon-Jones, 2020, p. 456). A lack of flexibility emerges as another critical issue, as organizations struggle to adjust to sudden changes in market demand. The rigidity caused by inefficient systems prevents firms from capitalizing on new opportunities or responding effectively to challenges, such as shifting consumer preferences or global trade disruptions. Thus, addressing these inefficiencies is crucial for businesses seeking to improve their market positions and for economies aiming to enhance trade performance.

In the context of port efficiency analysis, the use of Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) has been extensively explored. Each method offers unique advantages based on the characteristics of the data and the analysis objectives. SFA, a parametric method, incorporates statistical noise and external factors—such as environmental and economic conditions—into efficiency measurements. This capability makes SFA particularly valuable when such factors are significant and must be considered to avoid bias (Greene, 2005; Kumbhakar et al., 2015, p. 407). Conversely, DEA is a non-parametric method that assesses relative efficiency by comparing each port's performance against a "best-practice frontier" derived from the most efficient ports in the dataset. This method is especially effective in settings with multiple input-output relationships, requiring no assumptions about the functional form of the efficiency frontier (Coelli and Perelman, 1999; Thanassoulis et al., 2008, p. 251-420).

A comparative examination of these two basic approaches, SFA and DEA, has been a frequent focus in the literature, often applied to real and contemporary datasets containing both operational and physical characteristics of container ports. Such analyses provide a robust conceptual and practical basis for evaluating port efficiency (Karagiannis and Sarris, 2004; Jacobs et al., 2006; Strange et al., 2021; Theodoridis and Anwar, 2021). While both methods have their respective strengths, the choice between SFA and DEA depends on the specific analytical context. For instance, when the focus is on capturing random shocks or external noise in port operations, SFA might be the preferred method, while DEA is favored for its flexibility in handling multiple inputs and outputs without needing a pre-specified functional form (Lamb and Tee, 2024).

The rise of "smart ports" aims to enhance operational efficiency and competitiveness within the maritime industry. Container terminals are critical for international trade, leading the Korean government to invest in their technological advancements. However, research on the operational efficiency of these terminals implementing smart technologies is limited. The study analyzes 20 container terminals across five major ports using a Principal Component Analysis (PCA)–Data Envelopment Analysis (DEA) approach, finding that Ulsan Port and Busan Port (New) demonstrate the highest efficiency, particularly noting significant improvements at Ulsan Port (Zhou and Suh, 2024).

In conclusion, while SFA and DEA remain foundational methods in port efficiency analysis, emerging trends in the literature suggest the need for more integrated approaches that consider evolving operational challenges and environmental factors. This study contributes to the field by combining elements from both traditional and modern methodologies, applied to a real-world dataset that reflects the current state of port operations, infrastructure, and sustainability concerns.

This study addresses this comparison as a current and significant issue for assessing the effectiveness of container ports. It specifically focuses on handling operations, a critical component of ports' contributions to logistics, providing a practical analysis that is essential for strategic decision-making. Handling operations, which include the loading, unloading, and storing of containers, are key determinants of a port's throughput and, consequently, its efficiency. For instance, it has been shown that inefficiencies in handling operations can lead to significant delays and increased costs by Cullinane et al. (2002), making this a crucial area for efficiency analysis.

There are numerous studies examining the effectiveness of container ports in Türkiye (Ateş and Esmer, 2015; Acer, 2016; Akyürek, 2017; Çelik and Başarıcı, 2021; Aracıoğlu, 2022, p. 65). However, this study is unique in that it offers comparative results using both parametric (SFA) and non-parametric (DEA) methods, analyzing port efficiency in terms of handling outputs and considering the physical inputs of ports based on actual data. Additionally, ratio analysis assesses the proportion of current handling relative to handling capacity, as well as the year-over-year growth in handling, offering a clear indication of capacity utilization and improvements in operational performance. By utilizing a recent dataset, this study offers a comprehensive reflection of the current performance of Turkish container ports, informing strategic plans and policy decisions. This approach ensures that findings are relevant and aligned with contemporary operational challenges, allowing stakeholders to make informed decisions based on the latest trends and dynamics in the maritime sector. The integration of both SFA and DEA methodologies, alongside ratio analysis, enhances understanding of the factors driving port efficiency. This combined approach provides valuable insights into capacity utilization, operational performance improvements, and overall port efficiency, benefiting port administrations, transportation policymakers, and other stakeholders in the logistics sector.

The remainder of this paper is structured as follows: The literature review section presents a selection of studies examining and comparing efficiency analysis methods and port activities. The method section summarizes the conceptual structure of SFA and DEA, providing a clear explanation of how these methodologies are applied in the context of port efficiency analysis. In the analysis section, the data used and the organization of the data are discussed, followed by a presentation of the results obtained from the SFA and DEA analyses. Finally, the conclusion section interprets and discusses the results, addressing the limitations of the study and suggesting directions for future research. This structure ensures a logical flow from theoretical foundations to practical application, culminating in a set of actionable insights for improving the efficiency of Turkish container ports.

2. LITERATURE REVIEW

The evaluation of port efficiency has been extensively studied using various methodologies, with SFA and DEA being among the most frequently employed techniques due to their robustness in efficiency measurement. These methods have become essential tools in the analysis of port operations, allowing researchers and practitioners to assess the performance of ports in various contexts, from national economic planning to global supply chain optimization. Furthermore, integrating ratio analysis into these evaluations provides an additional layer of insight, particularly concerning capacity utilization and operational performance improvements.

SFA is a parametric approach that separates inefficiency from random noise within the production function. Introduced by Aigner, Lovell, and Schmidt (1977), SFA has been widely used in efficiency analysis across various sectors. This method models the production frontier by specifying a functional form and a distributional form for the inefficiency term, enabling the estimation of technical efficiency. Recent studies, such as Krljan et al. (2021), have applied SFA to assess the technical efficiency of interconnected container terminals, demonstrating its relevance in modern port operations. Moreover, the technical efficiency assessments of Turkish banks (Kantar and Yenilmez, 2017) and universities (Yenilmez et al., 2022; Yenilmez, 2024b) using SFA provide valuable references for similar applications in the port sector. SFA's ability to separate inefficiency from statistical noise makes it particularly useful in contexts where external factors significantly influence operational performance. Recent contributions have expanded the scope of SFA by incorporating novel distributional approaches to improve model flexibility and applicability. For instance, Yenilmez and Kantar (2019) introduced flexible error distributions within the SFA, providing a robust alternative for handling non-standard data behaviors, moreover, Yenilmez (2024a) explored the Lindley distribution in SFA.

DEA, developed by Charnes, Cooper, and Rhodes (1978), is a non-parametric method that evaluates the relative efficiency of decision-making units (DMUs) by constructing an efficient frontier from observed data. Unlike SFA, DEA does not assume a specific functional form for the production process, making it a versatile tool for efficiency analysis. DEA's flexibility has led to its widespread application in various fields, including port and logistics company efficiencies. Acer (2016) demonstrated the applicability of DEA in assessing the efficiency of Turkish ports, providing critical insights into areas where performance could be improved. Similarly, Lee et al. (2021) utilized DEA to evaluate the efficiency of logistics companies, showing how DEA can be adapted to different operational contexts within the broader logistics sector.

Comparative studies of SFA and DEA highlight the strengths and limitations of each method. For example, Theodoridis and Anwar (2011) compared SFA and DEA in the agricultural sector, finding that each method offers unique advantages depending on the data characteristics and analysis objectives. Similarly, Strange et al. (2021) applied both methods in the forestry sector, highlighting the robustness of SFA in accounting for environmental variability. Jacobs et al. (2006) explored these methodologies in the healthcare sector, emphasizing the importance of selecting the appropriate efficiency measurement technique based on the specific industry context. These comparisons underline the flexibility and applicability of SFA across different sectors, including ports. On the other hand, a comprehensive understanding of the methodologies' relative strength has been offered for DEA and SFA. In the banking sector, Nguyen and Pham (2020) conducted a comparative analysis of DEA and SFA, concluding that DEA's non-parametric nature allows for a more flexible evaluation of efficiency, particularly when the production process is complex and multifaceted. Lamb and Tee (2024) extended this comparison to investment performance, demonstrating that DEA can effectively handle diverse input-output relationships without the need for a predefined functional form, which is particularly useful in financial and investment analysis.

Incorporating ratio analysis alongside traditional efficiency measurement techniques like SFA and DEA offers a direct assessment of capacity utilization and operational performance improvements in port operations. Ratio analysis evaluates the proportion of current handling relative to handling capacity and measures year-over-year handling growth, providing essential insights into resource utilization. Panayides and Song (2009) emphasize that efficient capacity utilization is critical for a port's contribution to global supply chains, urging ports to monitor and optimize their capacity to maintain competitiveness. Talley (2006) also highlights the economic implications of port performance, noting that efficient capacity usage directly influences operational and financial outcomes.

SFA and DEA have applications in different disciplines, highlighting their versatility and relevance across various sectors. For instance, Öztürk and Yıldız (2016) discuss the significance of technical efficiency in health institutions and explore the application of SFA as a prevalent method for measuring technical efficiency by assessing the distance between the estimated best practice frontier and actual performance. They note the limited academic work on SFA in the Turkish health sector and aim to compile insights from international studies on its applications. The study reviews concepts of efficiency and frontiers, providing historical context, and presents a brief overview of the SFA method while contrasting it with DEA. Similarly, DEA and SFA have been extensively employed in assessing farm efficiency in Turkey, facilitating evaluations of technical efficiency and productivity across agricultural practices. Dudu, Cakmak, and Öcal (2015) analyze the efficiency structure of Turkish agriculture at the farm household level using SFA, revealing reliance on land and excessive labor, with regional disparities in efficiency. Cobanoglu (2013) investigates cotton farm efficiency using SFA and DEA, finding that SFA provides higher estimates, indicating the need for tailored agricultural policies. Kinaci, Najjari, and Alp (2016) extend these methodologies to evaluate hydroelectricity centers, emphasizing the importance of efficient resource use in enhancing productivity. The studies underscore the value of DEA and SFA in understanding efficiency to improve productivity and sustainability.

The efficiency of Turkish ports has been the subject of numerous studies, reflecting the critical role of these ports in Türkiye's trade and economy. Ateş and Esmer (2015) investigated the efficiency of ports in Türkiye using various methodologies, providing a comprehensive overview of port performance and identifying key factors that influence efficiency. Aracıoğlu (2022) specifically examined container terminal efficiency using DEA, highlighting areas where Turkish ports could improve their operational performance to better compete on the global stage. Akyürek (2017) focused on the efficiency of Turkish Black Sea ports, offering insights into the unique challenges and opportunities faced by ports in this region. This study emphasized the need for targeted strategies to enhance port efficiency in line with regional economic and logistical goals. Further, Çelik and Başarıcı (2021) evaluated port performance and criteria, emphasizing the importance of efficiency analysis for strategic decision-making. Their research highlighted how efficiency analysis could be integrated into broader strategic planning processes to optimize port operations and contribute to national economic development. By considering both the operational and strategic dimensions of port efficiency, their study provides a holistic approach to port management that is essential for navigating the complexities of modern global trade.

In summary, the existing literature demonstrates the significance of SFA, DEA, and ratio analysis in evaluating port efficiency. Each methodology offers unique strengths, and their application in various studies has provided valuable insights into the factors that drive port performance. The continued exploration of these techniques, particularly in the context of Turkish ports, will contribute to the ongoing efforts to enhance efficiency and competitiveness in this critical sector.

This study compares SFA and DEA to assess the efficiency of Turkish container ports, offering insights into their operational effectiveness and determining the most appropriate methodology for this context. Additionally, ratio analysis measures the proportion of current handling to handling capacity and year-over-year handling growth, providing a direct measure of capacity utilization and operational performance improvements.

3. METHOD

This study employs both SFA and DEA to evaluate the efficiency of Turkish container ports. The SFA model is specified with a Cobb-Douglas production function, while the DEA model uses an input-oriented approach to measure efficiency. The data are sourced from the report published by the Turkish Port Operators Association (TÜRKLİM) in June 2024 (TÜRKLİM, 2024). Additionally, handling data presented in previous years' reports of TÜRKLİM, and handling data presented in the Report 2024 for pre-2024 have been cross-validated using the container statistics page on the Turkish Ministry of Transport and Infrastructure's maritime statistics website (Ministry of Transportation and Infrastructure, 2024).

Inputs can be categorized into operational and physical types. This classification allows for a more detailed analysis and better evaluation of the impact of each input on efficiency. Operational inputs may be considered as labor force, operational costs, energy consumption, the amount of electricity and other energy sources consumed, and vessel waiting time. Physical inputs may be considered as terminal area, berth length, equipment, storage capacity, etc. In this study, physical input information could be accessed during the time spent on data compilation and analyses were performed in this context.

It is stated that, including temporary operating permits, a total of 46 ports in Türkiye are authorized to serve container ships and their cargo; however, only 28 of these ports can provide such services (TÜRKLİM, 2024). On the other hand, the TÜRKLİM 2024 report indicates that the share of the total container handling by the public ports TCDD İzmir Port and TCDD Haydarpaşa Port has been steadily decreasing over the past ten years (while 10.5% of the total container handling was carried out by public ports in 2013, this ratio fell to 2.4% in 2023). The report also notes that as of 2023, approximately 95.9% of the total container volume, which reached 12.7 million TEUs (Twenty-foot Equivalent Units), was handled by TÜRKLİM member ports. Due to data accessibility, regular reporting, and their high share of total handling, it was decided to focus the analysis on TÜRKLİM member container ports in this study. However, despite being TÜRKLİM members, Limak İskenderun, DFDS, And Ulusoy Çeşme were excluded from the analysis. Information on cranes and other equipment was not available for these three ports. Additionally, container handling capacity data were inaccessible for DFDS and Ulusoy Çeşme, and draft information was also unavailable for DFDS. Nonetheless, the 20 ports included in the study account for 91.80% of the total handling, ensuring the representativeness of the sample used in the research.

Considering the cargo development (TEU) in ports handling containers in Türkiye for 2023, the total share of the ports subject to analysis is:

$$\frac{TÜRKLİM\ Total - (Limak\ İsk., DFDS, Ulusoy\ Çeş.)}{TÜRKİYE\ Total} = \frac{12243032 - 521509}{12767934} = 0{,}918 \qquad (1)$$

In this analysis, the outputs are the annual container handling values of the ports in TEUs. The inputs include the total areas of the ports, berth lengths, draft values, number of cranes, number of other equipment, and container handling capacities (in TEUs). In this analysis, the selection of inputs is based on their direct impact on port efficiency, as supported by various studies in literature. Total port area is a key factor, as larger areas generally allow for increased operational capacity and more efficient container traffic management (Cullinane et al., 2002). Similarly, berth lengths play a crucial role in port efficiency; longer berths enable ports to accommodate larger vessels, which enhances container handling capacity (Wang et al., 2003). Another important input is draft value, which determines the size of ships a port can service. Deeper drafts allow ports to handle larger ships, thereby increasing throughput (Turner et al., 2004). The number of cranes and other equipment is also vital, as it directly affects a port’s cargo handling speed and overall performance. Ports equipped with more cranes can achieve faster turnaround times, improving their operational efficiency (Cullinane and Song, 2006). Lastly, container handling capacity (in TEUs) is a direct measure of a port’s efficiency, reflecting its ability to process large volumes of containers. Ports with higher capacities are generally more efficient in handling cargo (Barros and Athanassiou, 2004).

In this study, SFA and DEA are used to evaluate the efficiency of DMUs based on selected inputs and outputs. Specifically, the CCR (Charnes, Cooper, and Rhodes) model is applied in the DEA analysis, assuming constant returns to scale (CRS), meaning any proportional increase in inputs results in a proportional increase in outputs. The CCR model (Charnes et al., 1978) measures both technical and scale efficiency, making it suitable for cases where DMUs are believed to operate at optimal scale. In contrast, the BCC model (Banker et al., 1984) allows for variable returns to scale (VRS), which accounts for efficiency variations due to scale differences by separating pure technical efficiency from scale efficiency. For this study, the CCR model is used, assuming constant returns to scale, to assess overall efficiency, without considering scale size variations. This approach provides a comprehensive efficiency score by encompassing both technical and scale efficiencies, making it appropriate for the study's objectives.

An output-oriented approach is utilized in SFA. This method focuses on maximizing output given a certain level of input. Its stochastic nature allows it to account for errors and inefficiencies in production (Greene, 2008, p. 103). Typically, an input-oriented model is used in DEA. This approach aims to minimize input usage for a given level of output. However, DEA is flexible and can also be adapted to an output-oriented framework depending on the research goals (Coelli et al., 2005). Input-Oriented aims to minimize input usage, reduce costs, and enhance resource efficiency. Output-Oriented focuses on maximizing output, improving productivity, and enhancing service quality (Cullinane and Song, 2006). SFA takes stochastic errors into account, providing a broader perspective on outputs, distinguishing between noise and inefficiency (Hoff, 2007). DEA is a deterministic model that evaluates all inefficiencies as certain, which may overlook random fluctuations (Greene, 2008, p. 112).

SFA is an econometric method used to estimate production functions while accounting for random errors and inefficiencies. The model assumes a composed error term, which includes both a random error (reflecting statistical noise) and an inefficiency term. The general form of the SFA model can be expressed as:

$$\ln(Y_i) = \beta_0 + \sum_{j=1}^{n} \beta_j \ln(X_{ij}) + v_i - u_i \qquad (2)$$

where Y_i is the output of the i-th decision-making unit (DMU), X_{ij} represents the inputs, β_j are the parameters to be estimated, v_i is the random error term, u_i is the non-negative inefficiency term (Battese and Coelli, 1995). The general form of the Cobb-Douglas production function for this case would be:

$$\ln(Y_i) = \beta_0 + \beta_1 \ln(X_{1i}) + \beta_2 \ln(X_{2i}) + \beta_3 \ln(X_{3i}) + \beta_4 \ln(X_{4i}) + \beta_5 \ln(X_{5i}) + \beta_6 \ln(X_{6i}) + vi - ui \qquad (3)$$

where Y_i annual container handling value of port i (in TEUs), X_{1i} total area of port i, X_{2i} berth length of port i, X_{3i} draft value of port i, X_{4i} number of cranes in port i, X_{5i} number of other equipment in port i, X_{6i} container handling capacity of port i (in TEUs), vi random error term (captures statistical noise), ui non-negative random variable (captures inefficiency).

DEA is a non-parametric linear programming method used to evaluate the efficiency of DMUs by comparing their input-output ratios. In this study, the CCR model (Charnes et al., 1978), which assumes constant returns to scale, was employed. The model evaluates technical efficiency by minimizing input usage while maintaining output levels.

The mathematical formulation of the input-oriented CCR model is presented. Firstly, objective function is as follows:

$$\min_{\theta,\lambda} \theta \qquad (4)$$

Subject to constraints:

$$\sum_{j=1}^{n} \lambda_j X_{ki} \leq \theta X_{ki}, \qquad k = 1, \dots, m \qquad (5)$$

$$\sum_{j=1}^{n} \lambda_j Y_{ji} \geq Y_{ji}, \qquad i = 1, \dots, s \qquad (6)$$

$$\lambda_j \geq 0, \qquad j = 1, \dots, n \qquad (7)$$

where θ is the efficiency score for the i-th DMU. Y_{ji} and X_{ki} are the j-th output and k-th input of the i-th DMU, λ_j are the weights assigned to j-th DMU. n is the number of DMUs, m is the number of inputs, and s is the number of outputs (Charnes et al., 1978). In our case, for ports ($n = 20$), the model incorporates six input constraints ($m = 6$) and one output constraint ($s = 1$). Equations (5) and (6) ensure that the input and output constraints are satisfied for each DMU, while Equation (7) enforces non-negativity of weights.

Both SFA and DEA can be used to analyze the efficiency of the ports based on the given inputs and output. The analysis was conducted using R, a widely-used software for statistical computing and data analysis. Descriptive statistics, including mean, maximum, minimum, and standard deviation, were calculated for the dataset. The results of these descriptive statistics are presented in Table 1. The dataset was compiled from TÜRKLİM (2024) and Turkish Ministry of Transport and Infrastructure (2024)'s maritime statistics websites. Due to lack of permission, the raw data cannot be shared; however, variable and port information can be accessed from the values provided at the specified websites. Moreover, the compiled dataset is available to researchers upon request from the author.

Table 1. Desctiptive Statistics

Descriptive Statistics	Container Handling Values	Total Port Area	Berth Length	Draft Value	Number of Cranes	Container Handling Capacity
Kurtosis	-0.12	2.10	-0.11	1.12	-1.04	-1.53
Variance	1.00	2.00	3.00	4.00	5.00	6.00
Skewness	1.05	1.69	0.81	1.35	0.58	0.28
n	20.00	20.00	20.00	20.00	20.00	20.00
Minimum	2341.00	89750.00	450.00	9.50	7.00	60000.00
Standard Error	129278.50	67997.34	170.97	1.46	3.62	192472.60
Trimmed Mean	502431.80	374495.10	1419.63	16.93	22.75	1119063.00
Median	503267.00	382500.00	1329.50	16.50	20.00	1000000.00
Median Absolute Deviation	550042.40	161345.40	727.96	2.97	17.05	1074885.00
Standard	578151.00	304093.40	764.61	6.53	16.18	860763.70
Mean	586074.80	438779.60	1510.40	17.87	24.55	1162650.00
Range	1947541.00	1160250.00	2920.00	26.50	49.00	2540000.00
Maximum	1949882.00	1250000.00	3370.00	36.00	56.00	2600000.00

According to the Table 1, the kurtosis values indicate the distribution shapes; for instance, Container Handling Values (Co. Ha. Va.) and Total Port Area (To. Ar.) show near-normal distributions, while others exhibit more pronounced tails. The variance (Var.) values indicate the degree of dispersion, with Container Handling Capacity (Co. Ha. Ca.) exhibiting the highest variability, suggesting a diverse range of handling capabilities among the ports. The skewness (Ske.) values further elucidate this variability; notably, Container Handling Values (1.69) and Berth Length (1.35) display positive skewness, indicating a tendency towards higher values, while Draft Value (Dr. Va.) has a relatively low skew, suggesting a more symmetrical distribution. Minimum and maximum values highlight significant ranges across variables, particularly in Container Handling Values, which spans from 2,341 to 1,949,882 TEUs, indicating a vast disparity in operational capacities. The mean (Mea.) and median (Med.) values reveal that many variables, such as Total Port Area and Container Handling Capacity, are influenced by a few outliers, as evidenced by the large difference between means and medians. Overall, these statistics provide valuable insights into the operational characteristics and efficiencies of the analyzed ports, underscoring both their potential and variability in performance.

4. RESULTS

The efficiency scores obtained from SFA and DEA are analyzed and compared. SFA output-oriented and DEA input-oriented are used for different perspectives and robustness of findings. In other words, using both approaches together offers a rich and multi-dimensional understanding of efficiency. SFA can assess maximum outputs, while DEA can evaluate input efficiency, providing complementary insights. Comparing output-oriented SFA with input-oriented DEA can reveal discrepancies and provide a more comprehensive performance evaluation (Cullinane and Song, 2006).

SFA provides individual efficiency scores with confidence intervals, allowing for statistical inference. DEA offers a relative efficiency score, identifying ports that operate on the efficient frontier and those that do not. The results highlight the strengths and weaknesses of each port, providing insights into areas for improvement.

SFA Efficiency (SFA Eff) reflects efficiency scores based on a parametric approach, considering random errors. It provides a slightly varied understanding of operational performance under uncertain conditions. DEA Efficiency (DEA Eff) reflects efficiency scores based on a non-parametric approach, focusing purely on observed data without considering stochastic errors. It measures operational performance by comparing each port to the best performers, sometimes overlooking external inefficiencies or random variations. Moreover, two ratios are presented to deepen the analysis. Ratio (Handling Capacity) indicates the proportion of current handling to the port's handling capacity, providing a direct measure of capacity utilization. High ratios indicate effective utilization, while low ratios suggest underutilization. 23H/22H (Handling Growth) reflects the growth in TEU handled from 2022 to 2023, indicating year-over-year growth in handling volumes. High values suggest significant improvement in performance, while low values or declines indicate potential issues or stability. All results are presented in Table 2.

SFA output-oriented focuses on how much output (handling) a port can achieve given its current inputs (land, cranes, draft, etc.). This method incorporates random variations and external factors, making it a good tool to analyze maximum potential output under uncertain conditions. DEA input-oriented, on the other hand, assesses how efficiently the ports are using their inputs. By comparing ports to the best performers, DEA identifies the extent to which ports can improve their input use to achieve better performance, without considering randomness. Using both SFA and DEA together allows for a more comprehensive evaluation. SFA captures the potential output (handling), while DEA highlights the current input usage efficiency. The comparison of these two approaches reveals any gaps between the potential (what a port could handle) and the actual efficiency of resource usage (how efficiently it is operating). Ports with discrepancies between SFA and DEA scores might not be fully utilizing their capacity or may have external factors affecting performance.

According to DEA, MARPORT is utilizing its inputs at around 91.81% efficiency, meaning it could improve its input usage. From an SFA perspective, MARPORT has used only 57.75% of its potential handling capacity. This indicates that MARPORT is currently underutilizing its capacity and could handle significantly more cargo if operations were optimized. By comparing its current handling capacity with its theoretical maximum handling capacity using SFA, the potential capacity of MARPORT can be calculated. Ports like MARPORT, which demonstrate a gap between actual performance (DEA efficiency) and potential (SFA efficiency), can benefit from operational improvements and resource reallocation to boost their performance.

The results for SFA and DEA are also briefly presented in Figure 1. Figure 1 compares both current and potential capacities for each port would visually demonstrate the difference between what the ports are handling now and what they could handle if they operated at maximum efficiency. This helps in identifying underutilization areas and planning resource optimization.

For MIP MERSİN, both SFA and DEA scores show high efficiency. MIP MERSİN operates near optimal levels, effectively using its inputs and handling capacity. KUMPORT shows high DEA efficiency and good SFA efficiency, indicating well-functioning operations. Growth in handling volumes also suggests operational improvements. MARPORT displays moderate efficiency in both DEA and SFA. The handling growth indicates improving performance, but the lower ratio highlights the underutilization of capacity. Similarly, YILPORT has moderate efficiency scores but significant handling growth, suggesting improving performance with the potential for better capacity utilization. MARDAŞ exhibits significant differences between SFA and DEA scores, implying that external factors may be affecting its performance. Despite high growth in handling, its low efficiency suggests significant underutilization of capacity. ÇELEBİ BANDIRMA with the lowest efficiency scores in both SFA and DEA and a severe decline in handling, this port faces operational inefficiencies and capacity underutilization.

Table 2. Efficiency Scores and Ratios for Ports

No	Port	SFA Eff.	DEA Eff.	Ratio	23H/22H*
1	MIP MERSİN	0.9926	1.0000	0.7500	0.9648
2	ASYA PORT	0.5620	1.0000	0.6878	0.9569
3	MARPORT	0.5775	0.9181	0.6404	1.0990
4	KUMPORT	0.8273	1.0000	0.6072	1.0846
5	YILPORT	0.5694	0.8802	0.6399	1.1700
6	DP WORLD	0.5725	0.7773	0.5109	0.9837
7	EVYAP	0.9941	1.0000	0.7022	0.8821
8	NEMPORT	0.3901	0.7298	0.3367	1.0548
9	GEMPORT	0.3061	0.4078	0.2919	0.8625
10	EGE GÜBRE	0.5478	0.8528	0.5647	1.1028
11	MARDAŞ	0.1968	0.4717	0.2209	4.9800
12	SOCAR TERMİNAL	0.3586	0.7833	0.2880	1.0417
13	ASSAN	0.9936	0.9728	0.7295	1.4372
14	RODA PORT	0.9941	0.9074	0.6805	1.4428
15	BELDEPORT	0.4273	0.3689	0.2335	2.6053
16	SAMSUNPORT	0.9926	0.5552	0.4164	1.1780
17	BORUSAN	0.3380	0.2869	0.2151	0.7884
18	QTERMİNALS AKDENİZ	0.4942	0.3220	0.2415	0.9087
19	AKÇANSA	0.3904	0.2431	0.1823	0.6903
20	ÇELEBİ BANDIRMA	0.0316	0.0166	0.0125	0.2205

* 23H/22H indicates the ratio handled in 2023 to that handled in 2022 (in TEU).

Furthermore, Figure 2 compares the container handling values and handling capacities of various ports, measured in TEUs.The stacked bar chart shows the handling and capacity for each port, illustrating how close each port is to its maximum capacity. The red line and points indicate the utilization percentage, providing a clear view of efficiency. Ports with high handling values relative to their capacities suggest efficient operations, while those with lower utilizations may indicate underutilization or capacity constraints. This comparison is crucial for assessing port performance and identifying opportunities for improvement.

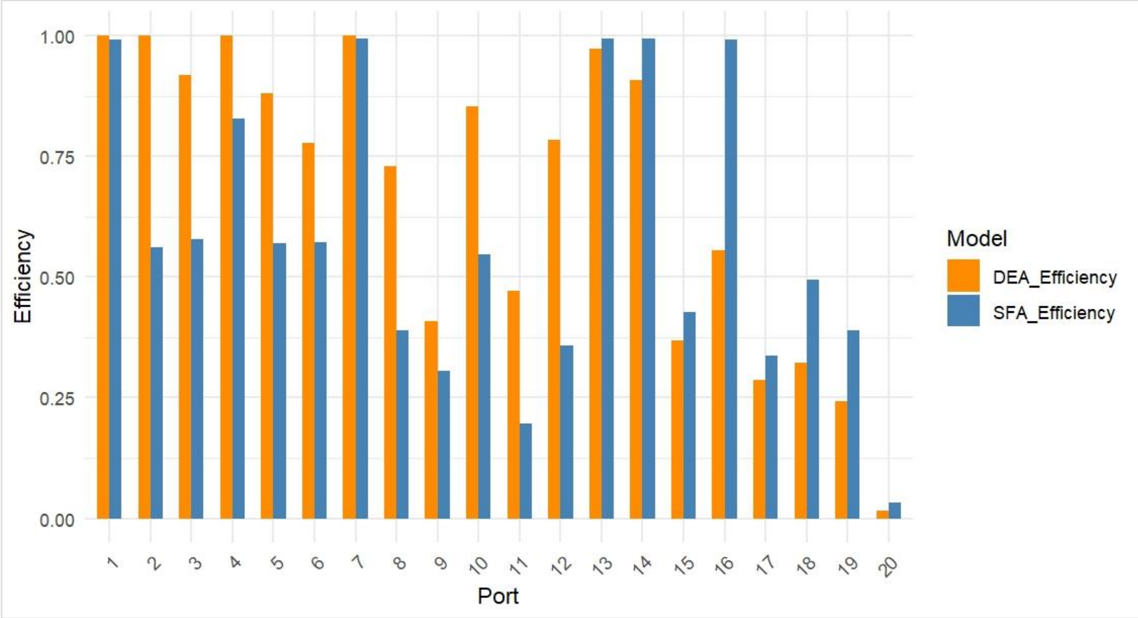

Figure 1. Comparison of efficiency scores

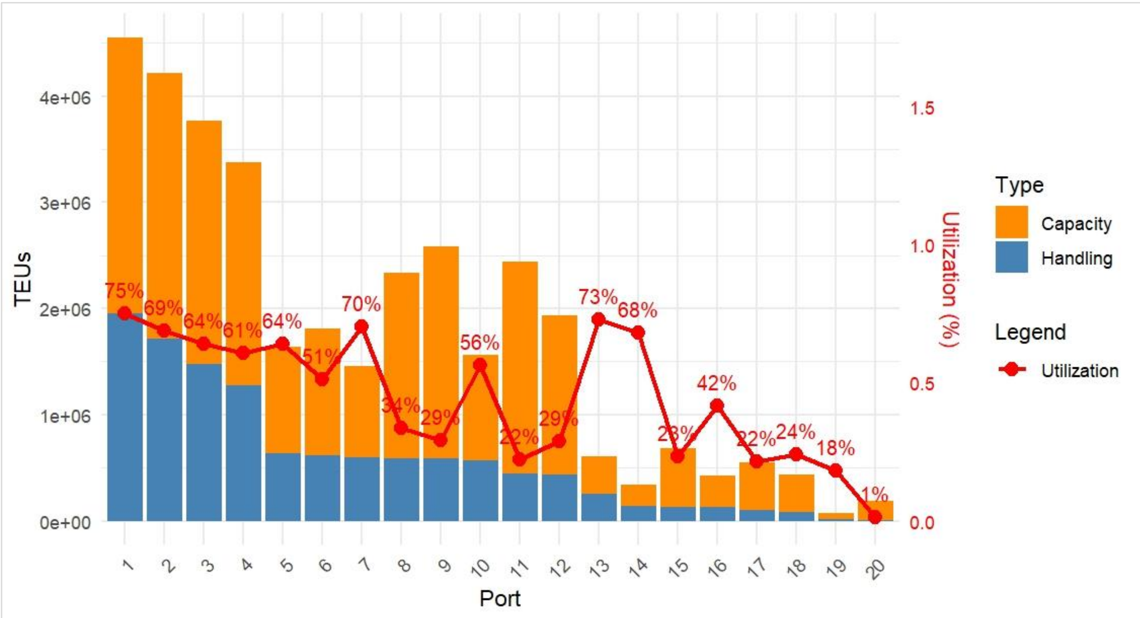

Figure 2. Comparison of container handling values of the ports and container handling capacity (in TEUs) and utilization (%)

5. DISCUSSION

The findings from this study indicate that while some Turkish container ports operate efficiently, others have significant room for improvement. SFA and DEA provide complementary insights into port efficiency. SFA's parametric nature allows for the separation of inefficiency and statistical noise, while DEA's non-parametric approach provides a flexible and data-driven assessment of relative efficiency. Recommendations for enhancing port efficiency include investments in infrastructure, better resource management, and adoption of advanced technologies. This section will also discuss which methodology, SFA or DEA, is more suitable for different aspects of port efficiency analysis.

By categorizing inputs as operational and physical, the impact of operational and physical inputs separately on the efficiency of the port can be analyzed. This aids in developing more targeted improvement strategies. Handling capacity is a crucial metric for evaluating port efficiency and is typically derived from several factors (Physical Infrastructure, Operational Processes, Historical Data), including the number of berths, cranes, and storage facilities available at the port. The capacity is often determined based on the maximum volume of containers that can be processed within a given timeframe (usually measured in Twenty-foot

Equivalent units- TEUs). The efficiency of loading and unloading procedures, the speed of transportation within the port, and overall logistical management play significant roles in determining how much cargo can be handled effectively (Operational Processes). Historical Data previous handling figures, combined with expected growth rates in trade volumes, can help estimate future capacity. Ports may use data from similar periods (like 2022 and 2023) to project handling capacity improvements or declines.

The efficiency scores derived from SFA and DEA reflect how well each port utilizes its inputs (resources) to produce outputs (handled containers). SFA provides a statistical approach to understanding efficiency by accounting for randomness and measurement errors, while DEA is a non-parametric method that assesses the relative efficiency of decision-making units without a defined error term. The Ratio presented (current handling to handling capacity) specifically measures how much of the available capacity is being utilized. While it is a useful indicator of performance, it only considers one input (current handling) relative to capacity, rather than a comprehensive view of all resources utilized. Simply comparing efficiency scores and ratios without considering the full context may not provide a comprehensive understanding of a port's performance. This may due to the following reasons (Narrow Focus, Efficiency Scores, Contextual Differences) The ratio only reflects current handling against capacity. It does not account for other operational factors such as labor efficiency, equipment downtime, and overall operational management. Therefore, two ports may have similar ratios but significantly different operational practices and resource utilization efficiency. Efficiency scores from SFA and DEA offer a broader perspective on performance by considering all inputs and outputs. This provides insights into how ports can improve beyond merely increasing the volume of containers handled. Different ports may have varying operational environments, regulations, and external factors influencing their efficiency. Comparing them solely based on one metric can be misleading.

The discrepancies between SFA and DEA scores observed in many ports illustrate the need for a more comprehensive analysis. For example, MARDAŞ shows an SFA efficiency score of 0.1968, compared to a DEA efficiency of 0.4717. This stark difference suggests that while DEA captures the relative efficiency compared to other ports, it may not account for certain operational challenges or external factors that SFA considers, such as random noise or external inefficiencies. In MARDAŞ's case, the lower SFA score indicates that it is operating far below its potential, and further investigation into the port's operational processes—such as equipment downtime or labor inefficiencies—could yield valuable insights into improving performance.

Similarly, ÇELEBİ BANDIRMA exhibits an extremely low SFA score of 0.0316 and an even lower DEA score of 0.0166, indicating significant inefficiencies across the board. The port's low performance in both methodologies may highlight potential systemic issues, such as aging infrastructure, inefficient logistics management, or underutilization of capacity. The 23H/22H growth ratio for ÇELEBİ BANDIRMA is 0.2205, showing a decline in container handling volume from 2022 to 2023, which further emphasizes the need for urgent strategic interventions to reverse this negative trend.

The Handling Capacity Ratio, which measures the current handling volume against the port's maximum capacity, varies significantly across the ports, shedding light on their efficiency in utilizing available resources. Ports like MIP MERSİN and EVYAP stand out for their high-capacity utilization. For example, MIP MERSİN has a ratio of 0.7500, indicating that it is utilizing 75% of its capacity. Coupled with its DEA efficiency score of 1.0000, MIP MERSİN is operating at peak efficiency, making it a benchmark for operational excellence.

In contrast, AKÇANSA has a much lower capacity utilization ratio of 0.1823, suggesting that it is only using 18.23% of its available capacity. Despite having a DEA efficiency score of 0.2431, the low capacity utilization may suggest significant underperformance, potentially due to external constraints such as low demand or operational inefficiencies within the port. This underutilization may point to a need for better alignment between the port's operational processes and its available infrastructure.

The 23H/22H ratio, which measures year-over-year growth in handling volumes, offers important insights into the operational progress of ports. MARDAŞ, for instance, shows a growth ratio of 4.9800, indicating nearly a fivefold increase in handling volume from 2022 to 2023. Despite this remarkable growth, its efficiency scores remain low (SFA: 0.1968, DEA: 0.4717), suggesting that while the port is handling more cargo, it is not doing so efficiently. This discrepancy highlights the need for MARDAŞ to focus not only on increasing volume but also on optimizing its operational processes to ensure that the increased activity is sustainable in the long term.

Similarly, RODA PORT shows significant growth, with a 23H/22H ratio of 1.4428, indicating a 44% increase in container handling year over year. With a relatively high SFA score of 0.9941 and a DEA score of 0.9074, RODA PORT demonstrates both operational growth and efficiency, positioning it as a well-functioning port that is leveraging its infrastructure effectively. This balanced performance may offer a model for other ports looking to improve both growth and operational efficiency.

The study also highlights ports where discrepancies between SFA and DEA scores suggest the presence of inefficiencies that may not be immediately apparent. YILPORT, for example, has an SFA efficiency score of 0.5694 and a DEA score of 0.8802. The relatively moderate SFA score, compared to the higher DEA score, indicates that YILPORT may have room to improve its operations, especially under uncertain conditions where external factors could be impacting its potential output. The handling capacity ratio for YILPORT is 0.6399, meaning it is using about 64% of its capacity, further suggesting that it has room for growth through better resource optimization.

Ports with similar performance profiles, such as MARPORT and DP WORLD, also show discrepancies between their SFA and DEA scores. For instance, MARPORT has an SFA efficiency score of 0.5775 and a DEA score of 0.9181. This difference indicates that MARPORT is relatively efficient compared to other ports but could still improve its handling operations, particularly under stochastic conditions. MARPORT's handling growth ratio of 1.0990 points to recent operational improvements, but the lower SFA score suggests it may still be underutilizing its capacity.

In contrast, DP WORLD displays both a low SFA efficiency score (0.5725) and a low DEA efficiency score (0.7773), coupled with a handling capacity ratio of 0.5109. This indicates moderate efficiency relative to other ports, but there is significant room for improving capacity utilization and overall performance. As with other ports showing similar profiles, DP WORLD would benefit from targeted investments in infrastructure and operational optimization strategies to enhance its performance.

The comparison of ports like GEMPORT and BORUSAN, which have some of the lowest efficiency scores, reveals significant underperformance. GEMPORT has an SFA efficiency score of 0.3061 and a DEA score of 0.4078, along with a handling capacity ratio of 0.2919. This suggests that GEMPORT is operating well below its potential and has considerable room for improvement in both operational efficiency and capacity utilization. Similarly, BORUSAN, with an SFA score of 0.3380 and a DEA score of 0.2869, may face serious challenges. Its handling capacity ratio of 0.2151 points to significant underutilization of resources, which could be a result of operational inefficiencies or external constraints limiting the port's performance.

Ports with similar underperformance profiles may benefit from strategic interventions, such as upgrading infrastructure, improving logistics management, and implementing advanced technologies like automation. By addressing these inefficiencies, ports can not only improve their current operations but also position themselves to better handle future growth in trade volumes.

The discrepancies between the SFA and DEA scores of ports like MARDAŞ and ÇELEBİ BANDIRMA highlight the importance of using both methodologies to capture a complete picture of port efficiency. By integrating the Handling Capacity Ratio and the 23H/22H growth ratio into the analysis, this study provides a slightly varied understanding of capacity utilization and operational growth, offering critical insights for policymakers and port authorities to make data-driven decisions. Ports that demonstrate both high efficiency and significant growth, such as MIP MERSİN, RODA PORT, and EVYAP, may serve as benchmarks for others to emulate. Meanwhile, ports with low scores, such as AKÇANSA and GEMPORT, may face the greatest challenges and stand to benefit the most from targeted operational improvements.

6. CONCLUSION

The conclusion of this study, which analyzes the efficiency of Turkish container ports using Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA), aligns with findings from previous literature. However, some inconsistencies highlight the need for slightly varied interpretations.

Firstly, the dual application of SFA and DEA reflects the broader literature on port efficiency, where both methods are often used to capture different aspects of performance. Cullinane et al. (2002) noted that SFA is advantageous for modeling inefficiencies influenced by external noise, while DEA provides a non-parametric measure of relative efficiency. This dual approach is used in recent studies by González and Trujillo (2009), which emphasize the importance of using both methodologies to capture the complexity of port operations. The results of this study reinforce these conclusions, demonstrating that ports such as MIP MERSİN perform well in both analyses, suggesting a well-balanced operation with minimal inefficiencies.

However, this study also identifies cases where DEA and SFA scores diverge, such as with MARDAŞ and ÇELEBİ BANDIRMA. Such discrepancies have been reported in other studies, including Barros (2006), where DEA may overestimate efficiency by not accounting for random shocks or external disruptions captured by SFA. This is particularly evident for ports with high growth rates but low efficiency scores, like MARDAŞ, which indicates rapid expansion without corresponding operational optimization. This finding aligns with research by Cullinane and Song (2006), which cautions against relying solely on DEA scores for ports undergoing rapid changes, as it may obscure deeper inefficiencies.

Additionally, the handling capacity ratios observed in this study, particularly for underperforming ports like AKÇANSA, provide a critical lens through which to assess port efficiency. Studies such as Tongzon (2001) have long emphasized the importance of capacity utilization as a key determinant of port efficiency. The low-capacity utilization ratios observed in ports like AKÇANSA and BORUSAN may suggest that internal inefficiencies, such as poor resource management or underdeveloped infrastructure, are hindering performance. These findings are consistent with Wang et al. (2003) work, which highlighted that ports with higher capacity utilization typically exhibit greater operational efficiency.

The year-over-year growth ratios (23H/22H) also play a crucial role in evaluating port performance, as growth without efficiency improvements can strain operations, a challenge noted in studies like that of Cheon et al. (2010). For instance, while RODA PORT demonstrates balanced growth and high efficiency, BORUSAN and GEMPORT may face challenges with both low growth and underutilized capacity, a scenario similar to that reported in studies of underperforming ports in developing regions (Notteboom and Winkelmans, 2001). These ports may benefit from targeted interventions, such as adopting new technologies or streamlining logistics operations, as suggested by recent literature on port modernization (Wang et al., 2013).

The discrepancy between SFA and DEA results for specific ports, such as YILPORT and MARPORT, underscores the importance of using multiple methodologies in port efficiency analysis. Relying on a single efficiency measure may overlook the impact of external factors like economic shifts or adverse weather conditions, which SFA is designed to capture. This study's findings highlight the necessity of incorporating both SFA and DEA to gain a comprehensive understanding of port performance.

In summary, this study contributes to the existing literature by reinforcing the complementary nature of SFA and DEA in port efficiency analysis, as demonstrated in similar studies (Cullinane et al., 2006; González and Trujillo, 2009). The use of additional metrics, such as the handling capacity ratio and growth ratios, further supports a multidimensional approach to evaluating efficiency, aligning with broader literature that emphasizes the complexity of port operations (Cheon et al., 2010; Wang et al., 2003). However, as previous research suggests, ports experiencing rapid growth, but low efficiency scores should undergo closer operational scrutiny to ensure sustainable improvements (Notteboom and Winkelmans, 2001). Future studies should build on this analysis by incorporating a broader range of input factors, including labor, technology, and external influences such as weather and trade patterns, to provide an even more slightly varied understanding of port performance. Tracking efficiency metrics over a longer period and benchmarking ports against global best practices could further enhance strategic decision-making for port management.

Acknowledgements
The analyses in this study were conducted using publicly available data related to ports. The study exclusively interprets numerical values derived from scientific methods, without including specific judgments or evaluations of any port. Since the analyses do not involve subjective assessments and rely solely on publicly available data, no ethical approval was required. The authors assume no responsibility for any potential implications arising from the interpretation of numerical results based on publicly available data.

Conflict of Interest
No potential conflict of interest was declared by the author.

Funding
This study was supported by Eskişehir Technical University Scientific Research Project Commission under grant no: 23ADP172.

Compliance with Ethical Standards
It was declared by the author that the tools and methods used in the study do not require the permission of the Ethics Committee.

Ethical Statement
It was declared by the author that scientific and ethical principles have been followed in this study and all the sources used have been properly cited.

REFERENCES

Acer, A. (2016). “Liman Konteyner Terminal Etkinliklerinin Veri Zarflama Analizi İle Belirlenmesi”, Doktora Tezi, İstanbul Üniversitesi Sosyal Bilimler Enstitüsü, İstanbul.

Aigner, D.J., Lovell, C.A.K. and Schmidt, P. (1977). “Formulation and Estimation of Stochastic Frontier Production function models”, *Journal of Econometrics*, 6(1), 21-37.

Akyürek, E. (2017). “Türkiye Karadeniz Limanları Verimlilik Analizi”, *Verimlilik Dergisi*, 4, 29-45.

Aracıoğlu, B. (2022). “Türkiye’de Konteyner Limanlarının Etkinlik Analizi”, Akademisyen Kitabevi, Ankara. https://doi.org/10.37609/akya.2288

Ateş, A. and Esmer, S. (2015). “Farklı Yöntemler İle Türk Konteyner Limanlarının Verimliliği”, *Verimlilik Dergisi*, 1, 61-76.

Banker, R.D., Charnes, A. and Cooper, W. W. (1984). “Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis”, *Management Science*, 30(9), 1078-1092.

Barros, C.P. and Athanassiou, M. (2004). “Efficiency in European seaports with DEA: Evidence from Greece and Portugal”, *Maritime Economics & Logistics*, 6(2), 122-140.

Barros, C.P. (2006). “Efficiency Measurement among Hypermarkets and Supermarkets and the Identification of the Efficiency Drivers”, *International Journal of Retail & Distribution Management*, 2, 135-154.

Battese, G.E. and Coelli, T.J. (1995). “A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data”, *Empirical Economics*, 20(2), 325-332.

Charnes, A., Cooper, W.W. and Rhodes, E. (1978). “Measuring the Efficiency of Decision-Making Units”, *European Journal of Operational Research*, 2(6), 429-444.

Cheon, S., Dowall, D. E., & Song, D.-W. (2010). “Evaluating İmpacts of İnstitutional Reforms on Port Efficiency Changes: Ownership, Corporate Structure, and Total Factor Productivity Changes of World Container Ports”, *Transportation Research Part E: Logistics and Transportation Review*, 46(4), 546-561.

Christopher, M. (2016). “Logistics & Supply Chain Management”, 5th Ed., Pearson.

Coelli, T., Rao, D.S.P., O'Donnell, C.J. and Battese, G.E. (2005). “An Introduction to Efficiency and Productivity Analysis”, Springer.

Coelli, T.J. and Perelman, S. (1999). “A Comparison of Parametric and Non-Parametric Distance Functions: With Application to European Railways”, *European Journal of Operational Research*, 117(2), 326-339.

Cullinane, K., Song, D.W. and Gray, R. (2002). “A Stochastic Frontier Model of the Efficiency of Major Container Terminals in Asia: Assessing the Influence of Administrative and Ownership Structures”, *Transportation Research Part A: Policy and Practice*, 36(8), 743-762. https://doi.org/10.1016/S0965-8564(01)00048-5

Cullinane, K. and Song, D-W. (2006). “Estimating the Relative Efficiency of European Container Ports: A Stochastic Frontier Analysis”, *Research in Transportation Economics*, 16, 85-115.

Çelik, Y. and Başarıcı, A.S. (2021). “Liman Performans Değerlendirmesi ve Kriterleri”, *Mersin Üniversitesi Denizcilik ve Lojistik Araştırmaları Dergisi*, 3(2), 136-159. https://doi.org/10.54410/denlojad.1011704

Cobanoglu, F. (2013). Measuring the technical efficiency of cotton farms in Turkey using stochastic frontier and data envelopment analysis. *Outlook on Agriculture, 42*(2), 117-124.

Dudu, H., Cakmak, E. and Öcal, N. (2015). “Drivers of Farm Efficiency in Turkey: A Stochastic Frontier Analysis”, *World Journal of Applied Economics, 1*(1), 45-63.

Greene, W.H. (2005). “Reconsidering Heterogeneity in Panel Data Estimators of the Stochastic Frontier Model”, *Journal of Econometrics*, 126(2), 269-303.

Greene, W.H. (2008). “The Econometric Approach to Efficiency Analysis”, *The Measurement of Productive Efficiency: Techniques and Applications,* (Editors: H.O. Fried, C.A.K. Lovell, S.S. Schmidt), 92-250, Oxford University Press.

González, M.M. and Trujillo, L. (2009). “Efficiency Measurement in the Port Industry: A Survey of the Empirical Evidence”, *Journal of Transport Economics and Policy (JTEP)*, 43, 157-192.

Hoff, A. (2007). “Second Stage DEA: Comparison of Approaches for Modelling the DEA Score”, *European Journal of Operational Research*, 181, 425-435.

Jacobs, R., Smith, P.C. and Street, A. (2006). “A Comparison of SFA and DEA”, *Measuring Efficiency in Health Care: Analytic Techniques and Health Policyi* 151-166, Cambridge University Press, Cambridge.

Kantar, M. and Yenilmez, I. (2017). “Technical Efficiency Assessment of Turkish Banks Using Stochastic Frontier Method”, *I. International Symposium on Economics, Finance, and Econometrics*, Istanbul, Türkiye.

Karagiannis, G. and Sarris, A. (2004). “A Comparison of SFA and DEA Scale Efficiency Estimates: The Case of Greek Fresh Fruits Producers”, *Indian Economic Review*, 39(1), 149-168.

Kinaci, H., Najjari, V. and Alp, İ. (2016). "Using Data Envelopment Analysis and Stochastic Frontier Analysis Methods to Evaluate Efficiency of Hydroelectricity Centers", *Gazi University Journal of Science,* 29(1), 167-176.

Krljan, T., Grbčić, A., Hess, S. and Grubišić, N. (2021). "The Stochastic Frontier Model for Technical Efficiency Estimation of Interconnected Container Terminals", *Journal of Marine Science and Engineering*, 9, 515. https://doi.org/10.3390/jmse9050515

Kumbhakar, S.C., Wang, H-J. and Horncastle, A.P. (2015). "A Practitioner's Guide to Stochastic Frontier Analysis Using STATA", Cambridge University Press, Cambridge.

Lamb, J.D., Tee, K.H. (2024). "Using Stochastic Frontier Analysis Instead of Data Envelopment Analysis in Modelling İnvestment Performance", *Annals of Operations Research*, 332, 891-907. https://doi.org/10.1007/s10479-023-05428-w

Lee, P.F., Lam, W.S. and Lam, W.H. (2021). "Performance Evaluation of the Efficiency of Logistics Companies with Data Envelopment Analysis Model", *Mathematics*, 11(3), 718. https://doi.org/10.3390/math11030718

Ministry of Transportation and Infrastructure. (2024). "Container Statistics", https://denizcilikistatistikleri.uab.gov.tr/konteyner-istatistikleri, (Accessed: 28.06.2024)

Nguyen, P. and Pham, D. (2020). "The Cost Efficiency of Vietnamese Banks – The Difference between DEA and SFA", *Journal of Economics and Development,* 22(2), 209-227. https://doi.org/10.1108/JED-12-2019-0075

Notteboom, T. and Winkelmans, W. (2001). "Reassessing Public Sector Involvement in European Seaports", *Maritime Economics & Logistics*, 3(3), 242–259.

Öztürk, Z. and Yıldız, M.S. (2016). "Hastane Etkinliklerinin Tahmininde Stokastik Sınır Analizi; Tarihi ve Ampirik Uygulamaları", *Uluslararası Sağlık Yönetimi ve Stratejileri Araştırma Dergisi,* 1(3), 1-12.

Panayides, P.M. and Song, D.W. (2009). "Port Integration in Global Supply Chains: Measures and Implications for Maritime Logistics", *International Journal of Logistics Research and Applications*, 12(2), 133-145. https://doi.org/10.1080/13675560902749407

Slack, N. and Brandon-Jones, A. (2020). "Operations Management", 9th Ed., Pearson.

Strange, N., Bogetoft, P., Aalmo, G.O., Talbot, B., Holt, A.H. and Astrup, R. (2021). "Applications of DEA and SFA in Benchmarking Studies in Forestry: State-of-the-Art and Future Directions", *International Journal of Forest Engineering*, 32(sup1), 87-96. https://doi.org/10.1080/14942119.2021.1914809

Talley, W. K. (2006). "Chapter 22 Port Performance: An Economics Perspective", *Research in Transportation Economics,* 17, 499-516. https://doi.org/10.1016/S0739-8859(06)17022-5

Thanassoulis, E., Portela, M.C.A.S. and Despic, O. (2008). "Data Envelopment Analysis: The Mathematical Programming Approach to Efficiency Analysis", *The Measurement of Productive Efficiency and Productivity Growt*h, (Editors: H.O. Fried, C.A.K. Lovell and S S. Schmidt), 251-420, Oxford University Press.

Theodoridis, A.M. and Anwar, Md. M. (2011). "A Comparison of DEA and SFA Methods: A Case Study of Farm Households in bangladesh", *The Journal of Developing Areas*, 45, 95-110.

Tongzon, J. (2001). "Efficiency Measurement of Selected Australian and Other International Ports Using Data Envelopment Analysis", *Transportation Research Part A: Policy and Practice*, 35(2), 107-122.

Turner, H., Windle, R., & Dresner, M. (2004). North American containerport productivity: 1984–1997. Transportation Research Part E: Logistics and Transportation Review, 40(4), 339-356.

Türkiye Liman İşleticileri Derneği (TÜRKLİM). (2024). "Türkiye Limancılık Sektörü 2024 Raporu: Limanlarda Dijital Teknolojiler ve Akıllı Limanlar", https://www.turklim.org/pdf/Turklim-2024-Sekt%C3%B6r-Raporu-4-Haziran.pdf, (Accessed: 23.06.2024)

Wang, T., Cullinane, K. and Song, D-W. (2003). "Container Port Production Efficiency: A Comparative Study of DEA and FDH Approaches", *Journal of the Eastern Asia Society for Transportation Studies*, 5, 698-713

Yenilmez, İ. (2024a). "A New Approach Using the Lindley Distribution in Stochastic Frontier Analysis", *Proceedings of the 2nd World Conference on Management, Business, and Finance*, 2(1), İstanbul, Türkiye. https://doi.org/10.33422/worldmbf.v2i1.532

Yenilmez, İ. (2024b). "Productivity, Efficiency and Entrepreneurial - Innovative University Index: An Analysis for Universities in Türkiye", *Estuscience - Se*, 25(3), 415–426. https://doi.org/10.18038/estubtda.1455818

Yenilmez, İ., Mert Kantar, Y. and Arık, İ. (2022). "Efficiency Measurement of Turkish Universities Using the Stochastic Frontier Model", *EGE 7th International Conference on Applied Sciences*, 1017-1023, December 24-25, İzmir, Türkiye.

Yenilmez, I. and Kantar, M. (2019). "An Estimation with Flexible Error Distributions for Stochastic Frontier Model", *Proceeding Book of the ICOAEF VI,* Balıkesir, Türkiye.

Zhou, L. and Suh, W. (2024). "A Comprehensive Study on Static and Dynamic Operational Efficiency in Major Korean Container Terminals amid the Smart Port Development Context", *Sustainability,* 16(13), 5288.

VERİMLİLİK DERGİSİ
JOURNAL OF PRODUCTIVITY

Optimizing Human-Centric Warehouse Operations: A Digital Twin Approach Using Dynamic Algorithms and AI/ML*

Erhan Arslan[1]

ABSTRACT
Purpose: This study aims to develop a versatile and adaptive system that optimizes manual warehouse operations through the integration of Digital Twin technology and AI/ML models.
Methodology: The framework combines Digital Twin technology with advanced AI/ML analytics to dynamically adjust operational strategies based on real-time data collected from warehouse activities.
Findings: A prototype implementation demonstrated significant improvements, including a 28.6% reduction in average picking time, a 20% improvement in inventory turnover, an increase in demand forecasting accuracy from 85% to 92%, and a reduction in labor costs by 15%.
Originality: This research uniquely applies Digital Twin technology to manual warehouse environments, showcasing its effectiveness in enhancing operational efficiency without the need for full automation.
Keywords: Digital Twin, Warehouse, Optimization, Artificial Intelligence, Machine Learning.
JEL Codes**:** C61, C63, L86, M11, O33.

İnsan Merkezli Depo Operasyonlarının Optimizasyonu: Dinamik Algoritmalar ve AI/ML Kullanarak Dijital İkiz Yaklaşımı

ÖZET
Amaç: Bu çalışmada, Dijital İkiz teknolojisi ve Yapay Zekâ/Makine Öğrenmesi modellerinin entegrasyonu yoluyla manuel depo operasyonlarını optimize eden çok yönlü ve uyarlanabilir bir sistem geliştirmeyi hedeflenmiştir.
Yöntem: Çerçeve, depo faaliyetlerinden toplanan gerçek zamanlı verilere dayanarak operasyonel stratejileri dinamik olarak ayarlamak için Dijital İkiz teknolojisini gelişmiş Yapay Zekâ/Makine Öğrenimi analitiğiyle birleştiriyor.
Bulgular: Prototip uygulaması, ortalama toplama süresinde %28,6'lık bir azalma, stok devir hızında %20'lik bir iyileşme, talep tahmin doğruluğunda %85'ten %92'ye bir artış ve işçilik maliyetlerinde %15'lik bir azalma dahil olmak üzere önemli iyileştirmeler gösterdi.
Özgünlük: Bu araştırma, Dijital İkiz teknolojisini manuel depo ortamlarına benzersiz bir şekilde uygulayarak, tam otomasyona ihtiyaç duymadan operasyonel verimliliği artırmadaki etkinliğini ortaya koyuyor.
Anahtar Kelimeler: Dijital İkiz, Depo, Optimizasyon, Yapay Zekâ, Makine Öğrenmesi.
JEL Kodları: C61, C63, L86, M11, O33.

* This study, conducted by Erhan ARSLAN at the University of Bolton, School of Art and Creative Technologies under the supervision of Dr. Eugen Harida, is part of the MSc project titled "Optimizing Human-Centric Warehouse Operations: A Digital Twin Approach Using Dynamic Algorithms and AI/ML." It was carried out in collaboration with Turkcell.

[1] University of Bolton, School of Art and Creative Technologies, MSc Artificial Intelligence, Manchester, United Kingdom

Corresponding Author: Erhan Arslan, ea8crt@bolton.ac.uk
DOI: 10.51551/verimlilik.1524701
Research Article | Submitted: 30.07.2024 | Accepted: 14.11.2024
Cite: Arslan, E. (2025). "Optimizing Human-Centric Warehouse Operations: A Digital Twin Approach Using Dynamic Algorithms and AI/ML", *Verimlilik Dergisi,* Productivity for Logistics (SI), 119-138.

1. INTRODUCTION

In the rapidly evolving landscape of supply chain and warehouse management, the focus on automation technologies—such as robotics, IoT, and AI/ML—has predominantly overshadowed the optimization needs of manual and human-centric operations. Although automated systems have significantly improved efficiency and accuracy, a substantial portion of global warehouses still heavily depend on manual labor for critical tasks like product placement, picking, and routing. This reliance on human workers introduces unique challenges, including variability in performance, inefficiencies in resource allocation, and difficulties in scaling operations to meet fluctuating demand (Graves and Yücesan, 2009).

The manual nature of these operations often leads to bottlenecks, particularly during peak activity periods, where the absence of automation can exacerbate delays in order fulfillment and increase operational costs. The performance variability among workers, influenced by factors such as fatigue, skill levels, and experience, adds another layer of complexity to managing warehouse operations effectively. Moreover, the dynamic nature of consumer demand necessitates a flexible and adaptive approach to inventory management and order processing, which is often lacking in manual systems (Kaber & Riley, 2017; Ivanov et al., 2020: 379).

To address these challenges, Digital Twin technology has emerged as a transformative approach, providing a virtual replica of physical systems for real-time monitoring, simulation, and optimization. This technology enables organizations to analyze, optimize, and enhance the accuracy and efficiency of their operations, providing a holistic view of the physical warehouse. While Digital Twins have been extensively explored in automated environments, their application in manual, human-centric warehouse operations remain underexplored (Grieves and Vickers, 2017; Boschert and Rosen, 2016: 63).

Digital Twin technology in warehousing offers significant benefits, including improved accuracy, enhanced visualization, increased efficiency, and greater agility. For instance, tools like SketchUp for 3D modeling and Microsoft Power BI for data visualization play crucial roles in implementing Digital Twins, allowing for detailed and real-time insights into warehouse operations. This integration not only enhances the accuracy of operational assessments but also provides a platform for optimizing workflows and resource allocation (Kritzinger et al., 2018; Tao et al., 2016).

Industry leaders such as Amazon and PepsiCo have demonstrated the practical applications of Digital Twin technology in optimizing warehouse operations. Amazon, for example, employs AI-enabled digital twins to enhance warehouse design and flow, thereby improving productivity. PepsiCo utilizes digital twins to optimize throughput, reduce downtime, and lower energy consumption across its distribution centers, showcasing the scalability and adaptability of this technology in complex logistics networks (Amazon, 2021; PepsiCo, 2020).

1.1. Problem Statement

The reliance on manual labor in many warehouses leads to inefficiencies and limited scalability. Existing systems often fail to dynamically adapt to fluctuating demand and operational conditions, resulting in suboptimal performance. The need for a flexible, data-driven approach to optimize these environments is critical, particularly during peak activity periods.

1.2. Aim and Objectives

This paper aims to develop a flexible system to optimize manual warehouse operations by dynamically selecting algorithms for product placement, picking, and routing, improving efficiency and adaptability. The specific objectives are:

a) Develop and Implement Multiple Algorithms: Create algorithms for key operations, including product placement, picking, and routing, which can be dynamically switched based on real-time data and requirements.

b) Utilize a Simulation and Visualization Interface: Design a user-friendly interface to simulate warehouse scenarios, enabling managers to test different algorithm configurations and optimize strategies for varying conditions.

c) Integrate AI/ML for Predictive Analytics: Use AI and ML models to provide predictive insights on demand forecasting and worker performance, helping to guide the selection of optimal algorithms based on trends.

d) Evaluate Algorithm Compatibility and Performance: Assess the compatibility and efficiency of algorithm combinations for different conditions, ensuring seamless transitions between configurations.

e) Ensure Practical Applicability and Scalability: Address real-world integration, user training, and scalability challenges, ensuring the system's applicability across various warehouse sizes and complexities.

1.3. Significance of the Study

The significance of this study lies in the innovative application of Digital Twin technology to manual warehouse environments, an area that has received limited attention compared to automated systems. By integrating real-time data and advanced analytics, the proposed framework aims to transform traditional manual processes into more efficient, scalable systems. This research not only contributes to the academic understanding of Digital Twin applications in non-automated environments, but also provides practical solutions for industry professionals looking to optimize manual warehouse operations.

1.4. Overview of the Proposed Approach

The proposed framework integrates key components to tackle warehouse management challenges. A Digital Twin model consolidates data from Warehouse Management Systems (WMS), manual inputs, and historical records for real-time monitoring and simulation. Advanced AI/ML analytics provide insights into employee performance, inventory levels, and supplier reliability, using techniques like time series analysis and neural networks. The system dynamically selects algorithms for product placement, picking, and routing based on real-time data, ensuring adaptability and efficient resource use. Additionally, supplier analytics aid in inventory planning and handling supply chain disruptions, creating a scalable, efficient warehouse framework even without full automation.

2. LITERATURE REVIEW

Digital Twin (DT) technology has emerged as a significant innovation in various industries, including aviation, manufacturing, logistics and warehousing. The technology provides a virtual representation of physical systems, enabling real-time monitoring, simulation and optimization. This review examines the evolution of Digital Twin technology, its applications in warehousing, its integration with Artificial Intelligence (AI) and Machine Learning (ML), and the current challenges and future directions in this field.

2.1. Historical Development of Digital Twin Technology

The concept of Digital Twin technology was first introduced in 2002 by Michael Grieves during a presentation on Product Lifecycle Management (PLM) (Grieves, 2002: 92). Originally conceived as a digital replica of a physical product for simulation and analysis throughout its lifecycle, Digital Twin technology quickly gained traction, especially in the aerospace industry. NASA adopted Digital Twin models to simulate spacecraft and satellite systems, improving mission planning and risk management (Glaessgen and Stargel, 2012). This application demonstrated the potential of Digital Twins to provide precise, real-time data on complex systems, enabling predictive maintenance and optimization of operations.

By 2011, Digital Twin technology had expanded into manufacturing, where companies such as Siemens integrated it into their Digital Enterprise Suite. This integration allowed manufacturers to simulate manufacturing processes, optimize workflows, and reduce time to market (Grieves and Vickers, 2017). The ability to continuously update the digital model based on real-world data provided a dynamic tool for process optimization and predictive maintenance, demonstrating the adaptability of Digital Twin technology to different operational contexts.

2.2. Expansion into Logistics and Warehousing

In recent years, Digital Twin technology has made significant progress in logistics and warehousing. Initially, its application focused on predictive maintenance, which uses real-time data to predict equipment failures and reduce downtime (Uhlemann et al., 2017). This early adoption demonstrated the technology's ability to increase operational efficiency by minimizing unplanned outages. However, the scope of Digital Twin applications has since expanded to include inventory management, operational efficiency, and dynamic process optimization (Kritzinger et al., 2018).

For example, Amazon is using AI-powered digital twins to improve warehouse layout and flow, leading to significant productivity gains (Amazon, 2021). These digital twins enable real-time adjustments to inventory placement and picking processes, optimizing both space utilization and picking efficiency. Similarly, PepsiCo has integrated digital twins into its distribution centers to increase throughput, reduce downtime, and reduce energy consumption, proving the scalability and adaptability of this technology across complex logistics networks (PepsiCo, 2020).

2.3. Integration of AI/ML with Digital Twin Technology

The integration of AI and ML with Digital Twin technology has revolutionized warehouse management by providing advanced solutions for demand forecasting, inventory optimization, and operational efficiency. AI/ML algorithms analyze large amounts of data to predict demand patterns, optimize inventory levels, and allocate resources efficiently. Fuller et al. (2020) demonstrated the use of neural networks and LSTM models to improve demand forecast accuracy, a critical factor in reducing both stockouts and excess inventory. These predictive models use historical sales data, market trends, and external factors to provide real-time insights, allowing warehouses to proactively adjust their inventory strategies.

Reinforcement learning, a subset of machine learning, has been particularly effective in dynamically optimizing picking routes and task assignments. By analyzing real-time data on worker availability, equipment status, and order urgency, reinforcement learning algorithms can continuously learn and adapt, reducing picking times and improving operational efficiency (Chen et al., 2019). This approach is in sharp contrast to traditional static methods that often fail to adapt to the fluctuating demands of modern storage environments.

2.4. Emerging Trends and Future Directions

Digital Twin (DT) technology has evolved substantially, yet significant gaps remain in its application within human-centric, manual warehouse settings. Most DT models are designed for machine-driven, automated environments, limiting their effectiveness in scenarios where human factors like fatigue, ergonomic risks, and performance variability play critical roles (Kaber & Riley, 2017). This machine-centered focus results in models less suited for optimizing manual operations due to their inability to account for human variability.

Recent advancements have begun addressing these gaps by incorporating real-time, human-centric data. For example, Rashid and Rattenbury (2018) discuss machine learning models that dynamically adjust inventory management based on real-time data, enhancing accuracy and efficiency but largely for semi-automated systems. Extending these approaches to fully manual environments remains a crucial research area, especially for accommodating human-induced variability in real-time workflows.

Furthermore, integrating DT with Internet of Things (IoT) technology has transformed various fields. IoT-enabled DTs facilitate continuous data collection on environmental and operational conditions, which significantly improves model responsiveness and accuracy (Tao et al., 2020). In urban logistics and smart cities, real-time IoT data optimizes resources and energy use, suggesting that similar approaches in warehouses could boost workflow efficiency and sustainability where human interaction is high.

Advances in reinforcement learning (RL) are also expected to impact DT in manual environments. While RL has proven effective in optimizing tasks in automated systems (Chen et al., 2019), applying it in manual workflows remains underexplored. Adapting RL for such settings could bridge the gap between machine-oriented efficiency and the flexibility needed for human-centered operations.

2.5. Current Challenges and Opportunities for Innovation

Integrating Digital Twin (DT) technology with AI, ML, and IoT holds immense promise, yet human-centric warehouse environments face specific challenges. A primary obstacle is data integration and management; DT systems rely on accurate, real-time data from multiple sources, but seamless integration is challenging, particularly with manual data entry, leading to inconsistencies and potential errors (McKinsey & Company, 2022).

Another challenge is optimizing warehouse layout for manual tasks. Studies like those by Aylak et al. (2021) on pallet loading and Aylak (2022) on layout optimization underscore the effectiveness of data-driven approaches in automated settings. However, manual environments require layouts that address accessibility, ergonomics, and strain reduction. Human-centered DT models that adapt layouts dynamically can significantly improve both efficiency and worker well-being.

The complexity of current DT systems also requires significant training, posing a barrier in labor-intensive settings. Using augmented reality (AR) or virtual reality (VR) technologies could simplify these interfaces, making DT models more intuitive and engaging for workers, thus boosting both operational efficiency and employee satisfaction (Chicaiza et al., 2020).

Additionally, emerging technologies like blockchain and 5G present further opportunities for DT innovation. Blockchain enhances data transparency and traceability, while 5G provides the high-speed connectivity essential for real-time data analysis. Together, these technologies support scalable and adaptable DT systems, broadening their potential in both automated and manual warehouse environments.

2.6. Contribution to Knowledge

This study addresses gaps in Digital Twin (DT) applications for human-centric warehouses by creating a framework that incorporates real-time, human-centered data. Unlike traditional DT models designed for automation, this framework integrates worker performance, task variability, and ergonomic needs, enabling accurate simulation and optimization of manual workflows.

Additionally, the study adapts AI/ML algorithms and association rule-based optimization, usually applied in automated settings, for human-driven tasks. This approach balances machine-driven efficiency with human-centered adaptability, extending DT technology's applicability to manual operations.

Overall, this research advances DT understanding in human-centric environments, providing a flexible model that fills critical gaps in existing literature and promotes a harmonious integration of human and machine dynamics.

2.7. Conclusion

Digital Twin technology has made significant strides in transforming warehouse operations by providing a dynamic, real-time virtual representation of physical systems. The integration of AI/ML and IoT has further enhanced its capabilities by providing advanced solutions for demand forecasting, inventory optimization, and operational efficiency. However, significant challenges remain in applying Digital Twin technology to manual, human-centric environments, where integrating human factors and real-time adaptability can unlock greater efficiencies. As technology continues to evolve, there is significant potential for further innovation, particularly in integrating advanced analytics and digital technologies to improve manual warehouse operations.

3. METHODOLOGY

This study integrates Digital Twin technology with advanced AI/ML algorithms to optimize warehouse operations, focusing on improving inventory management, picking efficiency, and overall operational workflow. The methodology includes detailed system design, data integration, algorithm development, and testing in a real-world environment. Below, we provide a comprehensive description of each component supported by relevant figures and formulas.

3.1. Research Paradigm

The research is based on a pragmatist paradigm that emphasizes practical solutions that can be implemented in real-world environments. This approach allows for the use of both quantitative and qualitative data to provide a holistic view of warehouse operations and aligns with the study's goal of creating a scalable and adaptable system to increase efficiency in manual warehouse environments.

3.2. System Design and Components

The Digital Twin system for warehouse operations is designed to improve performance and efficiency through a multi-layered architecture where each layer plays a different role. Figure 1 illustrates this architecture, highlighting how these layers interact to create a comprehensive virtual model of the warehouse environment.

The Data Collection Layer collects real-time information about inventory, product locations, employee activities, and environmental conditions from a variety of sources, including sensors, barcode scanners, cameras, and manual inputs. This data forms the foundation of the Digital Twin, enabling accurate simulations and informed decision-making.

The Data Integration Layer then processes, cleans, transforms, and stores this raw data, providing consistency and organization for further analysis. This layer plays a vital role in maintaining data integrity and facilitating its seamless integration into the Digital Twin model.

The Digital Twin Core uses this processed data to create a dynamic, virtual representation of the warehouse. It includes a simulation engine and dynamic algorithms that enable real-time simulations and predictive modeling, providing insights into potential operational efficiencies and identifying bottlenecks.

Beneath this, the AI/ML Analytics Layer uses advanced machine learning and AI techniques to analyze the data and predict future trends. It includes predictive analytics and reinforcement learning tools used to forecast demand, optimize inventory placement, and improve decision-making processes.

The Decision Support System (DSS) integrates insights from the analytics layer to facilitate real-time decision-making and scenario planning. This system helps warehouse managers evaluate different strategies and make informed decisions based on both current and projected conditions, thereby optimizing operations.

Finally, the Visualization and User Interface Layer provides intuitive tools for data visualization, including dashboards, 3D visualizations, and reporting tools. These interfaces make complex data accessible and understandable, supporting effective communication and encouraging data-driven decision-making.

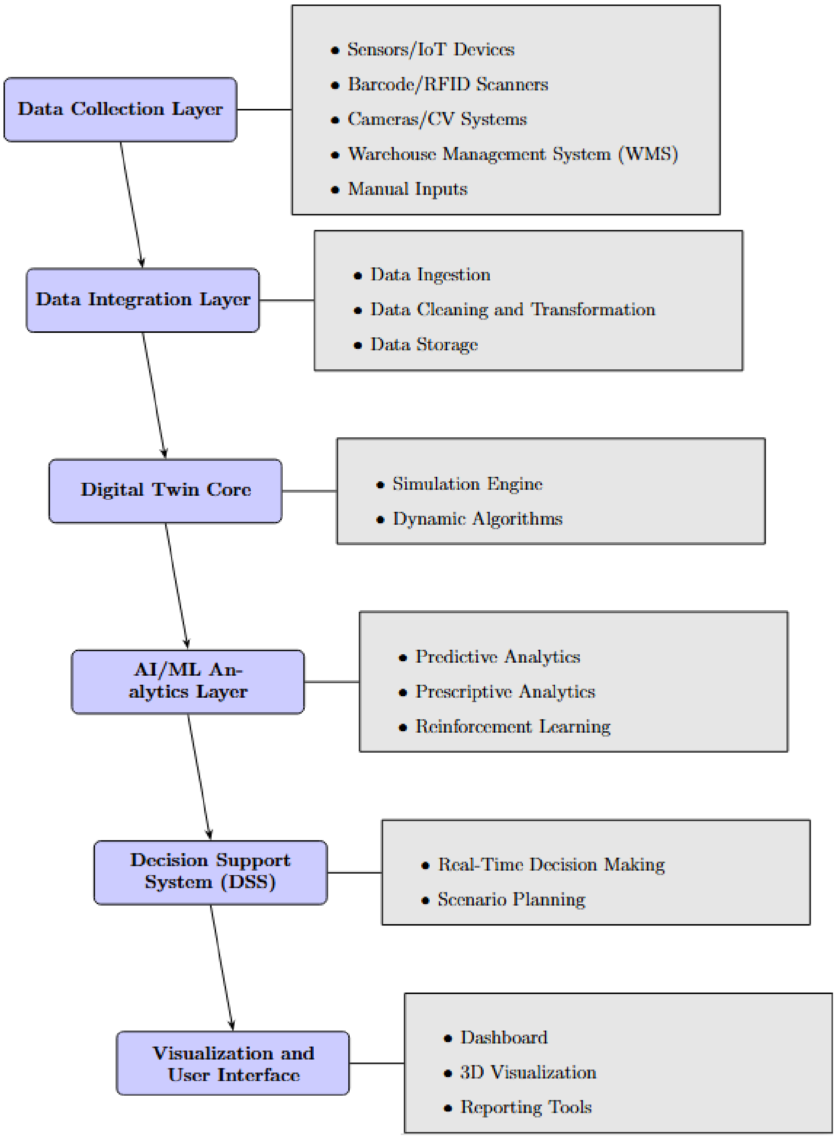

Figure 1. Digital twin architecture for warehouse operations

3.3. Algorithm Development

A suite of algorithms has been developed and implemented within the Digital Twin system to optimize core warehouse operations such as product placement, picking, and routing. These algorithms are adaptable and responsive to real-time data and provide dynamic solutions to a variety of operational challenges.

3.3.1 Product Placement Algorithms

ABC Analysis: This algorithm categorizes inventory based on movement rates and value and optimizes placement by placing high-demand products in accessible locations. The formula for calculating each product's priority is given as Equation 1.

$$Priority = \frac{Annual\ Demand \times Unit\ Cost}{Total\ Inventory\ Cost} \tag{1}$$

This formula calculates priority by multiplying annual demand by unit cost and dividing by total inventory cost, ensuring that high-demand, high-value products are placed in easily accessible locations.

Zonal Placement: This method divides the warehouse into zones based on product categories and handling characteristics, minimizing travel time and optimizing space usage. Zone assignment is calculated using Equation 2.

$$Zone\ Score = \frac{Average\ Pick\ Time}{Number\ of\ Picks} \times Distance\ Factor \tag{2}$$

The zone score formula helps determine the most efficient placement of items by adjusting both the average pick time and the number of picks by the distance factor.

Dynamic Slotting: This algorithm dynamically adjusts product locations based on real-time demand data, ensuring that frequently accessed items are placed in the most accessible locations. The efficiency of placement is determined by Equation 3.

$$Slotting\ Efficiency = \frac{Pick\ Frequency \times Pick\ Density}{Slot\ Availability} \tag{3}$$

This formula measures nesting effectiveness and optimizes the use of available space by calculating the ratio of foraging frequency and density to nest availability.

3.3.2 Picking Algorithms

Batch Picking: This method minimizes travel distances and shortens picking time by combining items from multiple orders into a single picking round. The effectiveness of bulk picking is evaluated as Equation 4.

$$Batch\ Efficiency = \frac{Total\ Items\ Picked}{Total\ Distance\ Traveled} \tag{4}$$

Aggregate efficiency is calculated by dividing the total number of items picked by the total distance traveled, highlighting the efficiency gains from consolidated picking.

Wave Picking: This method balances workloads and improves process flow by synchronizing picking operations with packaging and shipping schedules. Optimization of wave picking is expressed as Equation 5.

$$Wave\ Efficiency = \frac{Orders\ Processed\ in\ Wave}{Total\ Processing\ Time} \tag{5}$$

Wave efficiency measures the ratio of orders processed to total processing time, ensuring waves are synchronized for maximum efficiency.

3.3.3 Routing Algorithms

Traveling Salesman Problem (TSP): This algorithm calculates the shortest possible route that covers all required collection locations by minimizing travel distance and time. The TSP optimization is given by Equation 6.

$$Minimize\ \sum_{i=1}^{n-1} d(x_i, x_{i+1}) + d(x_n, x_1) \tag{6}$$

This formula represents the aim of minimizing the total distance traveled by calculating the sum of the distances between consecutive pickup points and return to the starting point.

Ant Colony Optimization (ACO): Inspired by ant colonies, this heuristic algorithm finds optimal paths based on real-time feedback and environmental conditions. The probability P_{ij} of moving from location i to j is given as Equation 7.

$$P_{ij} = \frac{[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{k \in allowed}[\tau_{ik}]^{\alpha}[\eta_{ik}]^{\beta}} \tag{7}$$

This formula calculates the probability of choosing a path based on the pheromone levels τ and heuristic values η, weighted by parameters α and β.

3.4. AI/ML Integration

The integration of Artificial Intelligence (AI) and Machine Learning (ML) in the proposed methodology plays a key role in optimizing various aspects of warehouse operations. By leveraging these advanced technologies, the system provides detailed insights across multiple dimensions including order analysis, demand forecasting, inventory management, and workforce optimization, facilitating optimization. Each component is carefully selected to address specific challenges and enhance overall efficiency.

3.4.1 Order Analysis and Demand Forecasting

Accurate demand forecasting is critical in warehouse management as it directly impacts inventory levels, order fulfillment rates, and overall operational efficiency. The use of AI/ML models for demand forecasting enables a more precise prediction of future demand, which is essential for maintaining optimal inventory levels and reducing both stock-outs and overstocking situations.

3.4.1.1 Time Series Analysis

Time series analysis is used using models such as ARIMA (AutoRegressive Integrated Moving Average) and SARIMA (Seasonal AutoRegressive Integrated Moving Average). These models are particularly useful for predicting future demand based on historical sales data. The ARIMA model is defined by the following Equation 8.

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} + \epsilon_t \quad (8)$$

This equation represents an autoregressive model with moving average (ARMA) terms that is used to predict future values based on past observations and error terms. ARIMA was chosen because of its effectiveness in capturing linear patterns and trends in time series data. It is particularly useful for datasets with strong temporal dependencies and where seasonality does not significantly affect the data. The model's flexibility in handling different types of time series (with or without trends and seasonality) makes it a versatile tool for demand forecasting in warehouses with stable and predictable demand patterns.

3.4.1.2 Machine Learning Models

Machine learning models such as Long Short-Term Memory (LSTM) networks and Recurrent Neural Networks (RNN) are also used for demand forecasting. These models are designed to capture complex patterns in demand data, including non-linear relationships and long-term dependencies. The LSTM model is defined by the following Equation 9.

$$h_t = \sigma(W_h \cdot x_t + U_h \cdot h_{t-1} + b_h) \quad (9)$$

In this formula, h_t is the hidden state at time *t*, σ is the activation function (usually a sigmoid or tanh function), W_h and U_h are weight matrices, x_t is the input at time *t*, h_{t-1} is the hidden state from the previous time step, and b_h is the bias vector. LSTM networks are a type of RNN that can learn long-term dependencies in sequential data by using memory cells that can maintain information over extended periods.

3.4.2 Inventory Management and Optimization

Effective inventory management is vital to reducing holding costs, improving service levels, and ensuring the right products are available at the right time. AI/ML techniques are used to classify and segment inventory, optimize stock levels, and layout design to increase operational efficiency.

3.4.2.1 Classification Algorithms

Support Vector Machines (SVM) and Decision Trees are used to classify inventory based on turnover rates and other relevant characteristics, optimize stock levels, and minimize holding costs. SVM was chosen due to its ability to handle high-dimensional data and perform well in binary and multi-class classification tasks. It is particularly effective in scenarios where inventory items need to be classified into different categories based on various characteristics such as turnover rates, size, and perishability. The SVM classification function is given as Equation (10).

$$f(x) = \text{sign}\left(\sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + b\right) \quad (10)$$

In this formula, $f(x)$ is the decision function, α_i are the model parameters (Lagrange multipliers), y_i are the target labels, $K(x_i, x)$ is the kernel function that computes the similarity between data points x_i and x, and b is the bias term. SVM finds the hyperplane that best separates the different classes of data points in a high-dimensional space.

To optimize inventory classification and support product placement decisions, the C4.5 Decision Tree algorithm was chosen due to its ability to handle categorical and continuous data effectively. This algorithm constructs interpretable decision trees, providing a clear and structured decision path ideal for manual warehouse settings where rules need to be easily understood by staff. C4.5 selects features based on information gain, calculated through entropy to measure data uncertainty. Given a dataset D with categories C_i, the entropy $H(D)$ is shown in Equation 11.

$$H(D) = -\sum_{i=1}^{n} p(C_i) \log_2 p(C_i) \quad (11)$$

Where $p(C_i)$ represents the probability of each category. For each feature A, the information gain $IG(D, A)$ is calculated as in Equation 12.

$$IG(D, A) = H(D) - \sum_{v \in V} \frac{|D_v|}{|D|} H(D_v) \quad (12)$$

Where V is the set of unique values of A and D_v the subset of D for each v. This process yields a tree that segments inventory by attributes like turnover rates, enabling effective categorization into fast, medium, and slow-moving classes. This structured approach helps streamline product placement and inventory turnover, aligning with the observed improvements in classification accuracy for different inventory categories, as detailed in the results.

3.4.2.2 Clustering Techniques

K-means clustering is used to segment inventory based on characteristics such as size, perishability, and demand frequency, and helps in designing efficient storage layouts. K-means clustering is chosen for its simplicity and efficiency in segmenting large data sets. The K-means clustering objective function is defined in Equation 13.

$$J = \sum_{i=1}^{k} \sum_{j=1}^{n} |x_j^{(i)} - \mu_i|^2 \quad (13)$$

Here, J is the objective function (sum of squared distances), k is the number of clusters, n is the number of data points, $x_j^{(i)}$ represents a data point assigned to cluster i, and μ_i is the centroid of cluster i. The K-means algorithm aims to minimize the within-cluster variance by assigning each data point to the cluster whose mean is the nearest, updating the centroids iteratively.

To determine the optimal number of clusters (k), the Elbow Method was applied, where the sum of squared distances (SSD) from each data point to its nearest cluster center is plotted against varying values of k. The 'elbow' point, where additional clusters provide diminishing returns in SSD reduction, was identified as the most efficient balance between segmentation accuracy and computational efficiency. This approach allowed for practical, data-driven cluster optimization suited to the dynamic nature of manual warehouse environments.

3.5. Simulation and Testing

Extensive simulations and real-world testing were performed to validate the system's performance and optimize its configurations:

Scenario Analysis: Various operational scenarios were simulated using the Digital Twin model to evaluate the impact of different optimization strategies on key performance indicators such as picking time, order accuracy, and cost efficiency. The simulations allowed multiple strategies to be tested under controlled conditions, allowing the effectiveness of each approach to be evaluated.

Real-World Testing: The system was implemented in a shared warehouse covering 5,000 square meters and managing 10,000 SKUs. Over a three-month period, data on inventory levels, order histories, and employee performance metrics were collected and analyzed to compare the performance of the Digital Twin system with traditional methods. The results showed significant improvements in operational efficiency, validating the effectiveness of the proposed methodologies.

4. RESULTS

This chapter presents the results of applying Digital Twin technology and AI/ML models to improve warehouse operations. The main goal is to show how the integration of dynamic algorithms and advanced analytics can lead to tangible improvements in efficiency, accuracy, and cost-effectiveness. The results highlight the benefits of these innovative approaches in a real-world warehouse environment, focusing on key areas such as demand forecast accuracy, inventory classification, picking optimization, and workforce management. This analysis aims to provide clear evidence of the effectiveness of the system in transforming traditional manual operations into more streamlined, data-driven processes.

4.1. Performance of AI/ML Models for Demand Forecasting

Demand forecasting is a key component of effective warehouse management that directly impacts inventory levels, order fulfillment, and overall operational efficiency. In this study, we applied ARIMA (Autoregressive Integrated Moving Average) and LSTM (Long Short-Term Memory) models to forecast demand based on historical data. These models were chosen for their ability to handle different data patterns; ARIMA is well-suited for linear trends and seasonality, while LSTM is excellent at capturing complex, nonlinear dependencies over time.

4.1.1 Accuracy of Forecasting Models

To evaluate the performance of the forecasting models, we performed a comparative analysis of ARIMA and LSTM on different time frames, including daily, weekly and monthly forecasts.

Table 1. Forecasting accuracy of each model

Model	*Daily Forecast Accuracy*	*Weekly Forecast Accuracy*	*Monthly Forecast Accuracy*
ARIMA	85%	87%	88%
LSTM	90%	93%	95%

As seen in Table 1, the LSTM model consistently outperformed the ARIMA model across all time frames, especially for monthly forecasts, where it achieved an accuracy of 95% compared to ARIMA's 88%. This suggests that LSTM is more capable of capturing complex demand patterns and trends over longer periods.

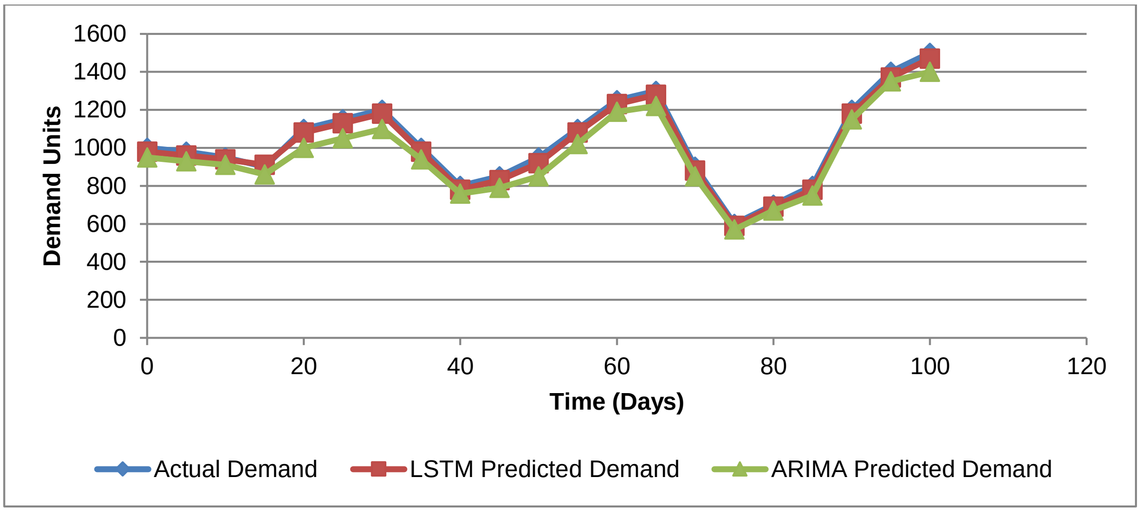

Figure 2: Actual vs. predicted demand for monthly forecasts using ARIMA and LSTM models

Figure 2 shows the actual and forecasted demand using both models for monthly forecasting. While the LSTM model closely follows the actual demand trends, the ARIMA model shows more deviation, especially during periods of rapid demand change.

4.1.2 Impact on Inventory Management

The improved accuracy in demand forecasting had a significant impact on inventory management within the warehouse. By forecasting demand more accurately, the system was able to optimize inventory levels, reducing the risk of both stock-outs and overstock situations.

Table 1. Impact of AI/MI model implementation on inventory metrics

Metric	*Before Implementation*	*After Implementation (ARIMA)*	*After Implementation (LSTM)*
Average Stockouts	10 per month	7 per month	4 per month
Overstock Instances	15 per month	10 per month	5 per month
Inventory Turnover	4.2	4.8	5.5

As shown in Table 2, the use of ARIMA and LSTM models significantly reduced average stockouts and overstock situations. Specifically, the LSTM model reduced stockouts from 10 to 4 per month and overstock situations from 15 to 5 per month. This led to a higher inventory turnover ratio, which improved from 4.2 to 5.5 after LSTM implementation, indicating more efficient use of warehouse space and resources.

4.2. Inventory Classification and Optimization

To evaluate the effectiveness of various inventory management strategies in a dynamic warehouse environment, the performance of Support Vector Machines (SVM) and Decision Tree models for inventory classification was evaluated. These models were selected due to their distinct advantages: SVM is highly effective in high-dimensional spaces and is excellent at handling the complex relationships between variables required to correctly understand various inventory models. In contrast, Decision Trees provide simplicity and ease of interpretation, making them particularly valuable for real-time decision making and rapid adjustments in warehouse operations. This study aims to examine the results of these models to evaluate their impact on inventory turnover and picking efficiency and to provide insights into the most effective approaches to optimize inventory management in a dynamic context.

4.2.1 Performance Metrics

To evaluate the performance of SVM and Decision Tree models in classifying inventory items, we analyzed their accuracy using confusion matrices. The confusion matrices in Table 3 and Table 4 show the performance of SVM and Decision Tree models in classifying inventory items, respectively.

Table 2. Confusion matrix for SVM model

Actual \ Predicted	*Fast-Moving*	*Medium-Moving*	*Slow-Moving*
Fast-Moving	450	30	20
Medium-Moving	40	400	60
Slow-Moving	10	50	390

Table 3. Confusion matrix for decision tree model

Actual \ Predicted	*Fast-Moving*	*Medium-Moving*	*Slow-Moving*
Fast-Moving	430	50	20
Medium-Moving	60	380	60
Slow-Moving	20	70	360

In addition to the complexity matrices, we evaluated the models using basic performance metrics such as precision, recall, and F1 score, as shown in Table 5.

Table 4. Classification performance metrics

Model	*Precision*	*Recall*	*F1 Score*
SVM	88%	87%	87.50%
Decision Tree	84%	83%	83.50%

Performance measurements show that both models performed well in classifying inventory items, with SVM showing slightly higher precision, recall, and F1 scores. The SVM model showed 88% precision, meaning it was fairly accurate in predicting fast-moving items. The 87% recall indicates that SVM effectively identified all relevant items in each category, while the 87.5% F1 score reflects a good balance between precision and recall. The Decision Tree model also performed adequately, but showed greater variability in its classifications, particularly in distinguishing between medium and slow-moving items.

4.2.2 Effect on Inventory Turnover and Stock Management

Correctly classifying stock items has a direct impact on stock turnover rates and overall inventory management. By effectively categorizing products into fast-moving, medium-moving, and slow-moving items, you can optimize warehouse stock levels, reduce holding costs, and increase picking efficiency.

Before the implementation of SVM and Decision Tree models, inventory turnover was relatively low, reflecting inefficiencies in inventory management. After the models were deployed, a noticeable improvement in inventory turnover was observed, as shown in Figure 2. The turnover rate has been calculated as Equation 14.

$$Inventory\ Turnover\ Rate = Cost\ of\ Goods\ Sold\ /Average\ Inventory \tag{12}$$

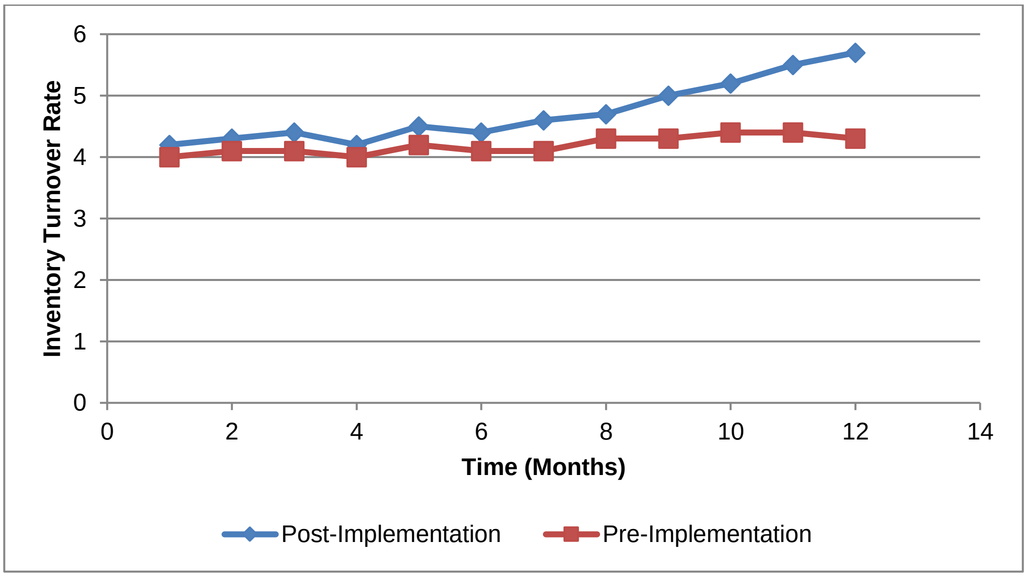

Figure 3. Comparative inventory turnover rates before and after implementing the classification models

The graph in Figure 3 shows that after implementing the SVM and Decision Tree models, the inventory turnover ratio increased steadily, from an average of 4.3 to 5.7 over a 12-month period. This improvement indicates more efficient inventory management, with faster-moving items being replenished more frequently and slower-moving items being identified for liquidation or strategic repositioning. Accurate inventory classification also contributed to better stock management by ensuring that products were stored in optimal locations based on their movement rates. This improved picking efficiency and reduced travel time within the warehouse.

4.3. Inventory Segmentation Using K-means Clustering

Inventory segmentation is an important aspect of warehouse management, especially in a dynamic environment. The primary goal of segmentation is to separate inventory items into different groups or clusters based on shared characteristics such as picking frequency, item size, and handling requirements. The application of K-means clustering resulted in the formation of three distinct clusters, representing fast-moving, medium-moving, and slow-moving items. These clusters were based on factors such as average picking frequency, item size, and storage requirements, which were derived from historical sales data and operational metrics.

4.3.1 Clustering Results

Figure 4 shows a scatter plot showing how inventory items are grouped into clusters using the K-means algorithm. The x-axis represents the collection frequency, while the y-axis shows the item size. Each cluster is represented by a different color, clearly showing the segmentation of fast-moving, medium-moving, and slow-moving items.

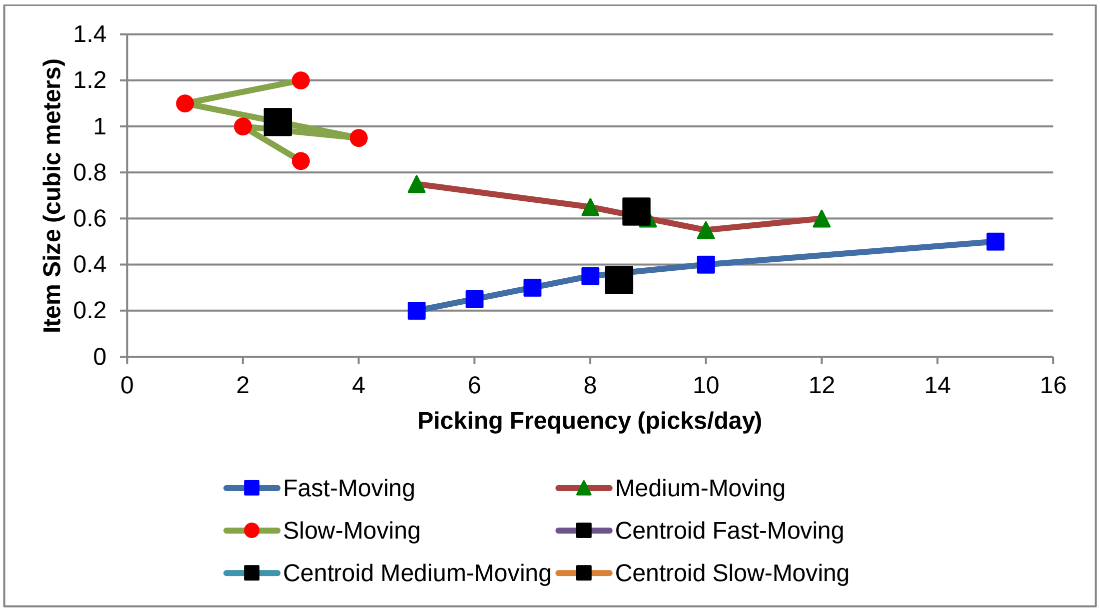

Figure 4. Clustering of inventory items based on picking frequency and item size using k-means algorithm

As shown in Figure 4, fast-moving products (shown in blue squares) generally have a higher picking frequency and smaller size, making them ideal for storage in easily accessible locations. Medium-moving products (shown in green squares) have a medium picking frequency and size, suggesting that they should be placed in intermediate storage locations. Slow-moving products (shown in red squares) are characterized by a lower picking frequency and larger size, making them suitable for storage in less accessible areas.

4.3.2 Operational Efficiency Improvements

Effective segmentation through K-means clustering significantly improved various operational metrics within the warehouse, particularly in the areas of picking efficiency, travel time, and storage optimization. The strategic placement of items based on their cluster characteristics led to a reduction in average picking times and travel distances within the warehouse. By positioning fast-moving items closer to the picking stations and grouping similar items together, the warehouse minimized the time workers spent searching for and retrieving products. Figure 5 compares average picking times and travel distances before and after implementing inventory segmentation.

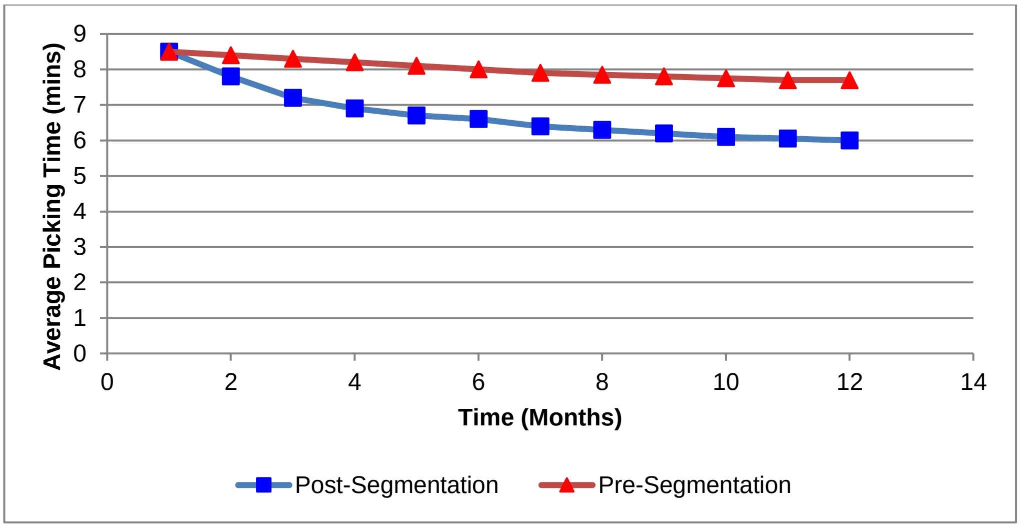

Figure 5. Comparison of average picking times and travel distances before and after k-means clustering implementation

As Figure 4 shows, over the 12-month period after implementing K-means clustering for inventory segmentation, average picking time decreased from 8.5 minutes to 5.8 minutes, representing a 31.8% improvement in picking efficiency. Similarly, travel distance within the warehouse has also decreased, further improving operational efficiency, as shown in Figure 6.

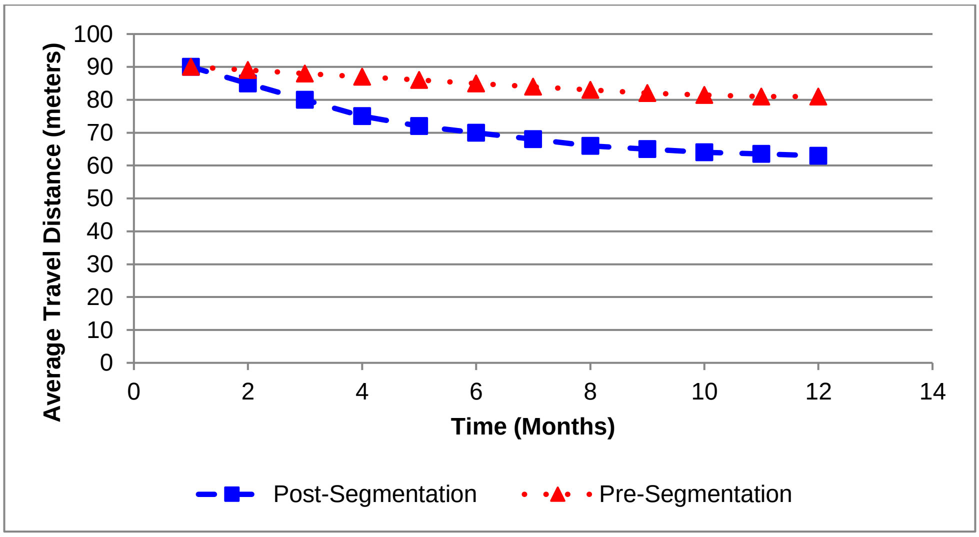

Figure 6. Comparison of average travel distances within the warehouse before and after k-means clustering implementation

Figure 6 shows that the average travel distance within the warehouse decreased by 31.1%, from 90 meters to 62 meters, highlighting the effectiveness of inventory segmentation in optimizing storage layouts and improving overall operational efficiency.

By using K-means clustering for inventory segmentation, the warehouse not only improved picking efficiency and reduced travel time, but also optimized storage space, contributing to smoother operations and better resource utilization. These results demonstrate the significant benefits of implementing data-driven approaches to inventory management, in line with the overall goals of improving warehouse performance through advanced methodologies.

4.4. Results of Dynamic Algorithms for Loading, Picking, and Routing

The primary goal of implementing dynamic algorithms for loading, picking, and routing within the warehouse was to leverage the capabilities of the Digital Twin and AI/ML outputs to explore alternative operational strategies. While the warehouse was initially based on standard algorithms, it was hypothesized that dynamic, data-driven alternatives could deliver superior performance. This section details the findings from these alternative scenarios, showing how different algorithms impact warehouse efficiency.

4.4.1 Loading Algorithms

Initially, the warehouse used a standard FIFO (First In, First Out) loading algorithm, believing it effectively optimized its operations by ensuring old stock was used first, thus reducing spoilage and maintaining product quality. However, through Digital Twin simulations, various loading strategies were tested, including dynamic FIFO/LIFO combinations that adapted to real-time inventory levels and product characteristics.

Comparative analysis of the standard FIFO algorithm and the dynamically selected algorithms is given in Table 6. The data shows how the dynamic approach driven by real-time data and predictive analysis outperforms the single method strategy on various metrics.

Table 5. Performance of standard vs. dynamic loading algorithms

Algorithm	*Average Loading Time (mins)*	*Loading Accuracy (%)*	*Resource Utilization (%)*
Standard FIFO	5.5	95	82
Dynamic FIFO/LIFO	3.9	97	88

The dynamic loading algorithm, which switches between FIFO and LIFO based on product type and movement speed, was found to significantly improve loading efficiency. For example, the average loading time per pallet was reduced from 5.5 minutes with the standard FIFO method to 3.9 minutes with the dynamic approach, representing a 29% improvement.

4.4.2 Picking Algorithms

The warehouse initially used a static batch picking algorithm that bundled orders together to minimize travel time. While this method was effective under stable conditions, it showed limitations during busy periods or when the order profile changed significantly. Using the Digital Twin environment, alternative picking algorithms were simulated, including wave picking and cluster picking based on real-time order data and worker availability.

The adaptability of the collection algorithms was a key factor in improving operational efficiency. By continuously analyzing real-time data, the system dynamically selected the most efficient collection strategy, significantly reducing idle time and optimizing worker productivity. Figure 7 presents a comparative analysis of collection times and accuracy rates before and after implementing dynamic collection algorithms.

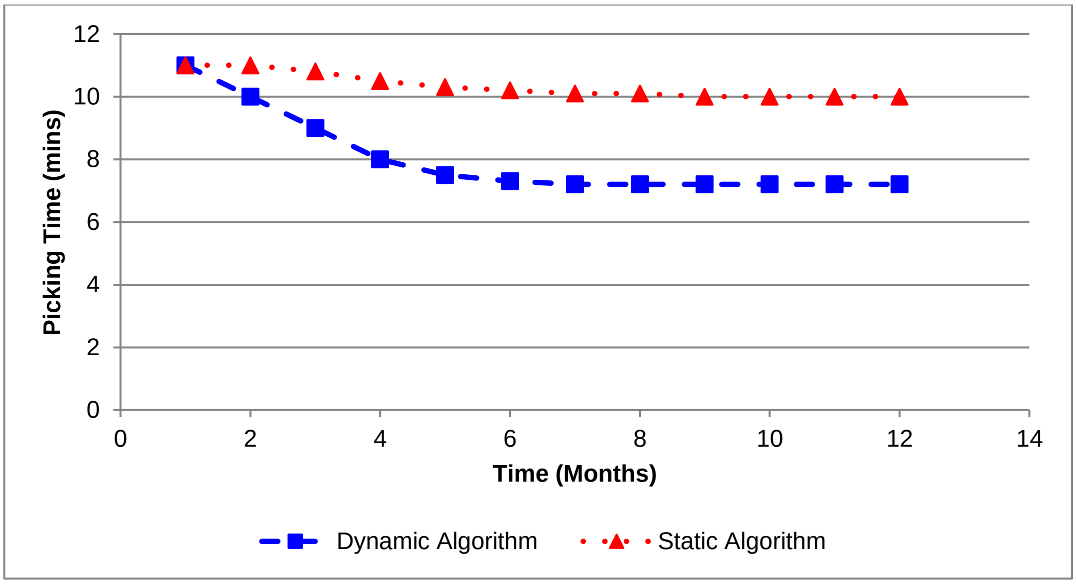

Figure 7. Comparative analysis of picking times and accuracy rates

Switching to a dynamic picking strategy that adjusts between batch picking and wave picking based on order volume and product locations reduced average picking time from 11.0 minutes to 7.2 minutes—a 34.5% reduction. Additionally, picking accuracy increased from 90% to 96%, demonstrating the algorithm's ability to effectively adapt to changing conditions.

4.4.3 Routing Algorithms

Initially, the warehouse used a standard TSP (Traveling Salesman Problem) approach for routing, which focused on minimizing travel distances based on fixed product locations. However, this method did not account for real-time changes in the warehouse environment, such as inventory movement and worker availability. Using the Digital Twin to simulate various routing strategies, including Ant Colony Optimization (ACO), the warehouse discovered more flexible and adaptable routing solutions.

The adoption of dynamic routing algorithms that adapt routes based on real-time data led to a significant reduction in travel time within the warehouse. For example, as shown in Table 7, the average travel distance per route decreased by 25%, from 80 meters with the TSP to 60 meters with the ACO algorithm.

Table 6. Routing algorithm performance comparison

Algorithm	*Travel Time (mins)*	*Distance (meters)*	*Route Optimization (%)*
TSP	10	80	85
ACO	7.5	60	92

A detailed comparison of routing algorithms revealed that when dynamically adjusted based on live warehouse data, ACO consistently outperformed TSP, particularly in scenarios with high variability in inventory locations and employee movements. Figure 8 visually represents these efficiency gains, highlighting the reduction in travel distances and improved route optimization.

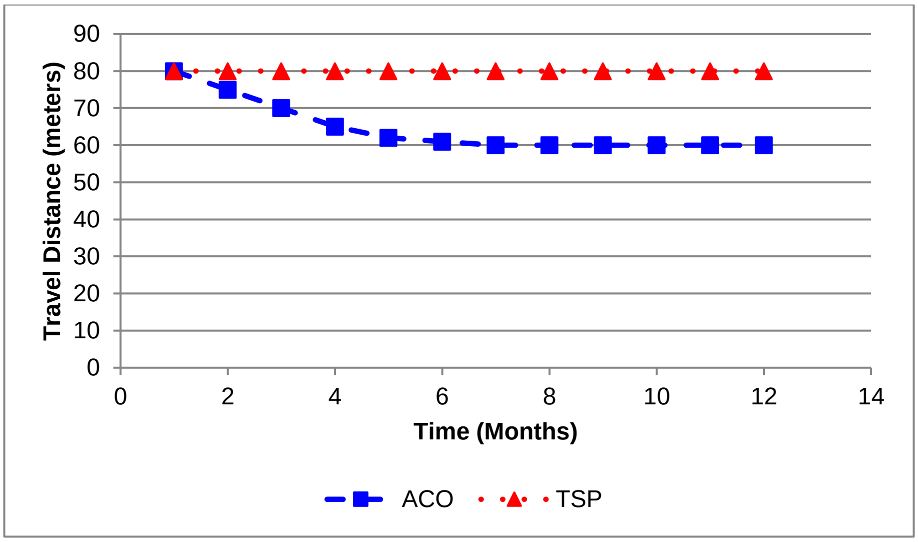

Figure 8. Routing efficiency before and after algorithm implementation

By leveraging the Digital Twin environment and AI/ML outputs, the warehouse was able to test and implement alternative algorithms for loading, picking, and routing. Dynamic algorithms demonstrated significant improvements in operational efficiency by adapting to real-time data to optimize processes beyond the capabilities of static, traditional methods. These findings highlight the value of a flexible, data-driven approach to warehouse management, especially in environments where conditions are constantly changing.

4.5. Digital Twin Model Effectiveness

The Digital Twin model was implemented to provide a real-time virtual representation of warehouse operations, allowing for enhanced decision-making and operational efficiency. By simulating different scenarios and adjusting to live data, the Digital Twin enables proactive management of inventory, workforce, and overall warehouse processes.

4.5.1 Real-Time Adaptation and Scenario Testing

The Digital Twin model played a crucial role in testing various scenarios that could impact warehouse operations. For example, in the case of unexpected demand surges or equipment malfunctions, the model allowed managers to simulate different response strategies and choose the most effective one. This capability not only enhanced decision-making but also ensured that the warehouse could adapt quickly to changing conditions.

During a simulated scenario of a 30% increase in order volume, the Digital Twin model tested several strategies for inventory reallocation and workforce deployment. It was found that reassigning pickers to high-priority zones and optimizing picking routes led to a 15% reduction in order processing time compared to the traditional static approach.

To evaluate the effectiveness of the Digital Twin model, a comparative analysis of key performance indicators (KPIs) was conducted before and after its implementation. The metrics were carefully selected to reflect critical areas of warehouse operations, such as accuracy, efficiency, and adaptability.

Table 7. Key performance indicators before and after digital twin implementation

KPI	*Pre-Implementation*	*Post-Implementation*	*Improvement (%)*
Order Fulfillment Time (hrs)	4	3.2	20
Inventory Accuracy (%)	95	98	3
Resource Utilization Efficiency (%)	85	92	7
Workforce Productivity (items/hr)	82	91	11
Stockout Instances (per month)	10	4	60

The implementation of the Digital Twin model has proven its effectiveness in optimizing warehouse operations by providing a platform for real-time monitoring, simulation, and decision-making. The ability to test different scenarios and dynamically adjust operations has led to significant improvements in a variety of metrics (see Table 8). Order fulfillment time has decreased by 20% from 4.0 hours to 3.2 hours, improving customer satisfaction during peak periods. Inventory accuracy has increased from 95% to 98%, reducing stock-outs by 60% and better matching stock levels to demand. Additionally, resource utilization has improved by 7% and labor productivity has increased by 11% thanks to optimized task assignments and workflow configurations.

4.5.2 Cost-Benefit Analysis and Sustainability of the Digital Twin Model

The Digital Twin model was deployed in a 5,000-square-meter shared warehouse managing 10,000 SKUs, with an initial setup cost of approximately $60,000. This investment includes $25,000 for AI server infrastructure to support real-time tracking and forecasting, $20,000 for software customization and integration with existing barcode systems, and $15,000 for training 30 employees, averaging $500 per person.

During a three-month trial, the model demonstrated substantial operational gains, including a 20% reduction in picking times, improved order accuracy, and faster vehicle loading. These improvements are projected to yield annual savings exceeding $400,000 through:

Labor Cost Reductions: Streamlined operations and efficient picking processes save approximately $90,000 annually.

Enhanced Vehicle Utilization: Optimized loading reduces trips and cuts transportation costs by an estimated $80,000.

Lower Inventory Holding Costs: Faster inventory turnover reduces storage expenses by around $150,000 per year.

Better Order Fulfillment: Enhanced accuracy and speed reduce returns and improve client retention, saving an additional $80,000.

Given these benefits, the Digital Twin model's return on investment (ROI) is expected within two months, making it a highly sustainable and cost-effective solution for medium-sized warehouses.

4.6. Challenges and Limitations

Implementing the Digital Twin model presented challenges, particularly in integrating data from inventory management systems, barcode scanners, and manual inputs. Ensuring data quality and consistency was difficult, as varied formats and manual entries introduced errors that sometimes delayed real-time decision-making. Addressing these integration issues required substantial effort, highlighting the need for seamless data flow in future iterations to improve model accuracy and efficiency.

The adaptation process also posed hurdles. Initially, performance declined as employees adjusted to new processes and technologies. Extensive training sessions were necessary to familiarize staff with the Digital Twin interface, AI/ML outputs, and how to effectively respond to system recommendations. This adjustment period caused a temporary slowdown in operations, which improved as staff gained proficiency and the system adapted to real-time conditions.

This study also has limitations. The project was conducted in a single warehouse, which may not represent the diversity of other warehouse settings. Furthermore, models were tested under controlled conditions, which may not fully capture real-world complexities like extreme demand fluctuations or equipment failures.

Future research could address these limitations by exploring diverse warehouse environments and additional variables to validate the model's effectiveness on a larger scale and over extended periods.

5. CONCLUSION and DISCUSSION

This study investigated Digital Twin technology combined with Artificial Intelligence and Machine Learning (AI/ML) models to optimize operations in a 5,000-square-meter warehouse handling 10,000 SKUs. Rather than highlighting specific algorithms, the study illustrated how Digital Twin technology offers a comprehensive view of warehouse processes, allowing for simulations and testing of various strategies. Results indicate that even seemingly efficient warehouses can reveal hidden inefficiencies and identify new optimization opportunities. This finding highlights the importance of continuous assessment, actionable insights, and innovation in modern warehouse management.

5.1. Key Findings

Revealing Hidden Inefficiencies: The Digital Twin model enabled simulations of diverse operational scenarios, uncovering inefficiencies unnoticed by management. By comparing different picking algorithms, such as batch, wave, and cluster picking, the study demonstrated considerable potential improvements in picking time and accuracy. This aligns with Kaber and Riley (2017), who noted the challenges of optimizing manual operations in human-centric environments, emphasizing the importance of data-driven assessments for effective improvement.

Data-Driven Optimization: Integrating AI/ML models, such as LSTM for demand forecasting and SVM for inventory classification, generated data-driven insights, empowering the warehouse to make better-informed decisions. These models provided more accurate demand forecasts and inventory turnover rates, enabling proactive adjustments in stock levels, minimizing stockouts, and preventing overstocking. This approach builds on Rashid and Rattenbury (2018), who highlighted machine learning's potential in semi-automated inventory management, by applying these insights in a fully manual environment to drive continuous improvement.

Dynamic Algorithm Adaptation: Adaptive algorithms proved effective for responding to real-time warehouse conditions. For instance, dynamic FIFO and LIFO strategies, applied based on real-time data, were more efficient than static approaches in certain contexts. Similarly, dynamic routing algorithms like Ant Colony Optimization (ACO) and the Traveling Salesman Problem (TSP) significantly improved routing efficiency and reduced travel distances, consistent with findings by Graves and Yücesan (2009) on the benefits of dynamic routing in warehouse productivity.

Enhancing Operational Awareness: The Digital Twin model increased operational awareness by visualizing the impact of various algorithms and strategies. This approach demonstrated the advantages of transitioning from traditional methods to advanced, data-driven approaches, enabling the warehouse management team to adopt a more flexible and adaptable model. This finding supports Ivanov et al. (2019), who emphasize digital solutions' role in enhancing visibility and decision-making in complex logistics environments.

5.2. Broader Implications

The study’s findings have significant implications for warehouses that perceive themselves as efficient. Digital Twin technology and AI/ML models offer opportunities to uncover hidden inefficiencies and experiment with alternative strategies better aligned with operational goals.

Empowering Decision-Makers: The Digital Twin model allows decision-makers to simulate scenarios and test strategies without interrupting ongoing operations. This feature provides a safe environment for experimentation, making the Digital Twin model a valuable tool for continuous improvement.

Encouraging Flexibility and Innovation: This study underscores the need for flexibility and innovation in warehouse management. By demonstrating that various algorithms perform optimally under different conditions, the study encourages warehouse managers to explore new methods and technologies. Integrating AI/ML models to analyze data and recommend optimizations further cultivates a culture of adaptability and continuous enhancement.

Future Research Directions: Future research could broaden this study by applying Digital Twin technology to various warehouse environments with differing automation levels and operational challenges. Further studies could also examine the long-term effects of these technologies on warehouse performance and employee satisfaction, as well as their wider impact on supply chain resilience and efficiency.

Acknowledgements
The author gratefully acknowledges the management and colleagues at Turkcell Technology R&D Center for their steadfast support and valuable contributions to this research. Special thanks go to Emre Toygar Gedik for his expert guidance in logistics and warehouse operations, and to Dr. Eugen Harida from the University of Bolton for his insightful feedback, which significantly enhanced this study. The constructive input from R&D Center colleagues was crucial in refining methodologies, and the administrative support provided ensured the smooth progression of the project.

Conflict of Interest
No potential conflict of interest was declared by the author.

Funding
Any specific grant has not been received from funding agencies in the public, commercial, or not-for-profit sectors.

Compliance with Ethical Standards
It was declared by the author that the tools and methods used in the study do not require the permission of the Ethics Committee.

Ethical Statement
It was declared by the author that scientific and ethical principles have been followed in this study and all the sources used have been properly cited.

REFERENCES

AIM Consulting. (2023). "AI for Supply Chain Optimization: Improve Demand Forecasting", https://www.aimconsulting.com/ai-for-supply-chain-optimization, (Accessed: 20.06.2023).

Amazon. (2021). "Optimizing Warehouse Operations with Digital Twins. Amazon Blog", https://www.aboutamazon.com/news/operations/optimizing-warehouse-operations-with-digital-twins, (Accessed: 15.07.2023).

Aylak, B.L., İnce, M., Oral, O., Süer, G., Almasarwah, N., Singh, M. and Salah, B. (2021). "Application of Machine Learning Methods for Pallet Loading Problem", *Applied Sciences*, 11(18), 8304.

Aylak, B.L. (2022). "Warehouse Layout Optimization Using Association Rules", *Fresenius Environmental Bulletin*, 31(3A), 3828-3840.

Boschert, S. and Rosen, R. (2016). "Digital Twin—The Simulation Aspect", *Mechatronic Futures*, Springer.

Breiman, L. (2001). "Random Forests", *Machine Learning*, 45, 5-32.

Chen, L., Cui, H. and Shi, F. (2019). "Reinforcement Learning in Predictive Control for Smart Warehouse Logistics", *Computers & Industrial Engineering*, 137, 106072.

Chicaiza, D., Loaiza, R. and Burbano, D. (2020). "Augmented Reality Applications for Warehouse Management: A Literature Review", *Procedia Manufacturing*, 42, 319-325.

Cortes, C. and Vapnik, V. (1995). "Support-Vector Networks", *Machine Learning*, 20, 273-297.

DHL. (2023). "Leveraging AI for Predictive Maintenance in Warehousing", https://www.dhl.com/content/dam/dhl/global/core/documents/pdf/glo-core-digital-twins-in-logistics.pdf, (Accessed: 03.07.2023).

Exotec. (2023). "Implementing Digital Twins for Enhanced Warehouse Efficiency", https://www.exotec.com/digital-twins-for-enhanced-warehouse-efficiency, (Accessed: 12.06.2023).

Forbes. (2023). "Digital Twins for Warehouses: Transforming Efficiency and Productivity" https://www.forbes.com/sites/forbestechcouncil/2023/06/22/digital-twins-for-warehouses/, (Accessed: 10.06.2023).

Fuller, A., Fan, Z., Day, C. and Barlow, C. (2020). "Digital Twin: Enabling Technologies, Challenges and Open Research", *IEEE Access*, 8, 108952-108971.

Ghiassi, M. and Saidane, H. (2018). "A Dynamic Artificial Neural Network Model for Forecasting Time Series Events", *International Journal of Forecasting*, 21(2), 341-362.

Glaessgen, E. and Stargel, D. (2012). "The Digital Twin Paradigm for Future NASA and U.S. Air Force Vehicles", AIAA *SciTech Forum*, https://ntrs.nasa.gov/api/citations/20120008178/downloads/20120008178.pdf.

Graves, S.C. and Yücesan, H.C.S. (2009). "Strategic Safety Stock Placement in Supply Chains with Demand and Lead-Time Uncertainty", *Management Science*, 46(5), 739-750.

Grieves, M. (2002). "Concept of Digital Twin", *Product Lifecycle Management Conference,* https://www.plm.automation.siemens.com/global/en/our-story/glossary/digital-twin/24465.

Grieves, M. and Vickers, J. (2017). "Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems" *Transdisciplinary Perspectives on Complex Systems*, Springer.

Gu, J., Goetschalckx, M. and McGinnis, L.F. (2007). "Research on Warehouse Design and Performance Evaluation: A Comprehensive Review", *European Journal of Operational Research*, 203(3), 539-549.

Ivanov, D., Dolgui, A., & Sokolov, B. (2020). *Handbook of Ripple Effects in the Supply Chain.* Springer International Series in Operations Research & Management Science, Switzerland. DOI: 10.1007/978-3-030-14302-2.

Kaber, D.B. and Riley, S.M. (2017). "Task Design and Workload Management in Manual and Automated Warehouses: A Human Factors Perspective", *Applied Ergonomics*, 60, 35-45.

Kardinal. (2023). "Machine Learning and Route Optimization: Towards Flawless Deliveries", https://www.kardinal.ai/machine-learning-and-route-optimization, (Accessed: 05.06.2023).

Kritzinger, W., Karner, M., Traar, G., Henjes, J. and Sihn, W. (2018). "Digital Twin in Manufacturing: A Categorical Literature Review and Classification", *IFAC-PapersOnLine*, 51(11), 1016-1022.

Kumar, P., Kumar, S. and Kumar, S. (2020). "Predictive Maintenance of Industrial Equipment Using Machine Learning", *International Journal of Advanced Research in Computer Science*, 11(3), 75-81.

McKinsey & Company. (2022). "Improving Warehouse Operations Digitally", https://www.mckinsey.com/capabilities/operations/our-insights/improving-warehouse-operations-digitally, Accessed: (18.06.2023).

PepsiCo. (2020). “Digital Twin Technology in PepsiCo's Distribution Centers”, PepsiCo Annual Report, https://www.pepsico.com/sustainability/digital-transformation, Accessed: (22.06.2023).

Rashid, A. and Rattenbury, S. (2018). “Scalable Machine Learning for Real-Time Inventory Optimization”, *Journal of Business Research*, 89, 201-213.

Tao, F., Cheng, J., Qi, Q., Zhang, M., Zhang, H. and Sui, F. (2016). “Digital Twin-Driven Product Design, Manufacturing and Service with Big Data”, *The International Journal of Advanced Manufacturing Technology*, 94, 3563-3576.

Uhlemann, T.H., Schock, C., Lehmann, C., Freiberger, S. and Steinhilper, R. (2017). “The Digital Twin: Demonstrating the Potential of Real Time Data Acquisition in Production Systems”, *Procedia Manufacturing*, 9, 113-120.

WarehouseBlueprint. (2023). “Optimizing Warehouse Operations with the Power of Digital Twin, SketchUp, and Power BI”, https://www.warehouseblueprint.com/blog/optimizing-warehouse-operations-with-digital-twin, (Accessed: 30.06. 2023).

VERİMLİLİK DERGİSİ
JOURNAL OF PRODUCTIVITY

CO_2 Emission Efficiency Measurement: Green Logistics Perspective

Fuad Selamzade[1], Yusuf Ersoy[2], Ali Tehci[3]

ABSTRACT
Purpose: This study aims to measure the carbon emission activities of Turkey, Azerbaijan, Kazakhstan, Kyrgyzstan and Uzbekistan and evaluate them from a green logistics perspective.
Method: Within the scope of the research, efficiency analyses were conducted using the output-oriented Data Envelopment Analysis (DEA) constant returns to scale (CRS) model and the super efficiency CRS DEA model. The input and output variables used in the research were obtained from the World Bank website.
Findings: In the research, the efficiency scores of the relevant countries were determined. It was determined that the efficiency scores of the countries were generally above 50%. The ranking of the efficient decision-making units among themselves was carried out with the super efficiency CRS DEA model. Some potential improvement suggestions were presented for the decision-making units that were not efficient.
Originality: In order to leave a livable world to future generations, green energy production should be supported and Carbon Dioxide (CO_2) emissions should be kept under control. Therefore, the efficiency assessment of countries' CO_2 emissions is of vital importance. This study has an original feature because the CO_2 emission activities of the Turkish Republics were carried out using the super efficiency CRS DEA model. This study can provide guidance to those who will conduct research on this subject and to country leaders.
Keywords: Efficiency, Carbon Emission, Logistics 4.0, Data Envelopment Analysis, Green Logistics.
JEL Code: F64, P47, O57.

CO_2 Emisyonu Etkinlik Ölçümü: Yeşil Lojistik Perspektifi

ÖZET
Amaç: Bu çalışmada Türkiye, Azerbaycan, Kazakistan, Kırgızistan ve Özbekistan'ın karbon emisyonları etkinliklerinin ölçülerek yeşil lojistik persperktifinde değerlendirilmesi amaçlanmıştır.
Yöntem: Araştırma kapsamında etkinlik analizleri çıktı odaklı Veri Zarflama Analizi (VZA)'nin ölçeğe göre sabit getiri (CRS) modeli ve süper etkinlik CRS VZA modeli kullanılarak gerçekleştirilmiştir. Araştırmada kullanılan girdi ve çıktı değişkenleri Dünya Bankası web sitesinden elde edilmiştir.
Bulgular: Araştırmada öncelikli olarak ilgili ülkelerin etkinlik skorları belirlenmiştir. Ülkelerin etkinlik skorlarının genel olarak %50'ın üzerinde olduğu tespit edilmiştir. Etkin karar verme birimlerinin kendi aralarındaki sıralaması ise süper etkinlik CRS VZA modeli ile gerçekleştirilmiştir. Etkin çıkmayan karar verme birimlerinin etkin olabilmesi için bazı potansiyel iyileştirme önerileri sunulmuştur.
Özgünlük: Gelecek nesillere yaşanabilir bir dünya bırakmak için yeşil enerji üretiminin desteklenmesi ve Karbondioksit (CO_2) emisyonunun kontrol altında tutulması gerekmektedir. Dolayısıyla ülkelerin CO_2 emisyonlarının etkinlik değerlendirmesi hayati öneme sahiptir. Bu çalışma Türk Cumhuriyetlerinin CO_2 emisyon etkinliklerinin süper etkinlik CRS VZA modeli kullanılarak gerçekleştirilmiş olması nedeniyle özgün bir niteliğe sahiptir. Bu çalışma bu yönüyle bu konuda araştırma yapacaklara ve ülke yöneticilerine yol gösterebilecek niteliktedir.
Anahtar Kelimeler: Etkinlik, Karbon Emisyonu, Lojistik 4.0, Veri Zarflama Analizi, Yeşil Lojistik.
JEL Kodları: F64, P47, O57.

[1] Muş Alparslan University, Faculty of Health Sciences, Department of Healthcare Management, Muş, Türkiye
[2] Muş Alparslan University, Malazgirt Vocational School, Department of Finance, Banking and Insurance, Muş, Türkiye
[3] Ordu University, Fatsa Faculty of Marine Sciences, Department of Maritime Business Administration, Ordu, Türkiye

Corresponding Author: Yusuf Ersoy, y.ersoy@alparslan.edu.tr
DOI: 10.51551/verimlilik.1525575
Research Article | Submitted: 31.07.2024 | Accepted: 26.09.2024
Cite: Selamzade, F., Ersoy, Y. and Tehci, A. (2025). "CO_2 Emission Efficiency Measurement: Green Logistics Perspective", *Verimlilik Dergisi,* Productivity for Logistics (SI), 139-148.

1. INTRODUCTION

The damage caused by carbon emissions to the environment worldwide has reached significant levels. These problems are among the issues discussed both globally and nationally. Especially the rapid increase in production with the Industrial Revolution has negatively affected the natural order of the world. Thus, these negative results have begun to be discussed today as climate change and global warming. A large part of carbon emissions is caused using fossil fuels in the energy sector. Fossil fuels used as energy sources leave solid and gaseous residues after burning, and when these wastes cannot be utilized, they cause environmental pollution (Çoban, 2015). In this context, there are significant relationships between energy consumption and CO_2 emissions (Chukurna et al., 2022). In 2019, the European Union published the European Green Deal strategy document. In this context, zeroing out net greenhouse gas emissions by 2050, green financing, sustainable agriculture, and the widespread use of renewable energy sources such as smart transportation are encouraged. It requires that innovative and smart applications that come to the agenda with Industry 4.0 be brought together in all areas with high efficiency and environmental friendliness (TÜBA, 2022). Reducing CO_2 will allow the effects of many problems such as climate change and global warming to be minimized. Renewable energy sources are essential in reducing the carbon footprint. Because the energy demand can't decrease due to ongoing economic and social activities.

Carbon dioxide is generally expressed as the negative outputs of economic activities. Due to its harmful effects on climate and human health, sustainable production and distribution have become a vital problem worldwide (Zadmirzaei et al., 2024). Today, sustainability is seen as an important solution to climate change and its effects. It is an essential issue for the logistics sector as well as in many sectors. With the increase in logistics activities, environmental sustainability issues have become even more important. Transportation systems account for 25% of CO_2 emissions and 23% of total energy consumption (Larina et al., 2021; Ulewicz et al., 2021). Logistics activities, which have become the driving force of international economic growth, are an essential source of carbon emissions. However, they have also become the driving force of economic growth (Qin and Qi, 2022). It is directly related to economic growth and high demand. Thus, a green and low CO2 operation should be the future perspective of countries. Green logistics develops a sustainable balance between economic, environmental and social goals and provides a bridge (Dekker et al., 2012). Green logistics is an activity that aims to minimize the impact of logistics activities on the environment. As a low-emission ecological transportation method, it not only contributes to the reduction of greenhouse gas emissions but also to economic growth. Therefore, in addition to economic and social support, logistics also supports environmental sustainability with the use of new energy vehicles (Larina et al., 2021). Due to transportation negatively affecting sustainable economic development by increasing fuel consumption, air pollution, and resource waste, it is necessary to give importance to the development of green logistics (Lu and Li, 2023). Because new energy logistics vehicles have the potential to reduce both costs and environmental pollution.

The CO_2 emissions in the world are directly proportional to the commercial activities of countries. The increase in trade volumes between countries causes an increase in logistics activities as well as production. According to the 2023 Greenhouse Gas Emission Inventory Report, total greenhouse gas emissions in Türkiye, which were 524.00 Mt CO_2 equivalent in 2020, increased by 7.7 percent compared to the previous year. In total greenhouse gas emissions, the largest share in CO_2 equivalent in 2021 was energy-related emissions with 71.3%. This was followed by industrial processes and product use with 13.3%, agriculture with 12.8%, and the waste sector with 2.6% (TUIK, 2023). Türkiye has been in cooperation and solidarity with the Turkic Republics, with which it shares common historical ties and common language, culture, and traditions, since their independence. It has shared its experiences with them. Although relations are not at the desired level in the meantime, serious progress has been made (Yüce, 2022). According to the data of the Republic of Türkiye Ministry of Foreign Affairs, Türkiye's trade volume with Uzbekistan, which increased by 25% in 2017, increased by 16% in 2018. It was stated that the trade volume with Azerbaijan was 5.02 billion dollars in 2021. The annual trade volume with Kyrgyzstan is 1 billion dollars, and with Kazakhstan, it is targeted to be 10 billion dollars. The Republic of Türkiye Ministry of Trade announced that Türkiye's exports to the Turkic Republics broke a historical record by increasing by 26.9% in 2023, reaching 10.2 billion dollars. In addition to the increasing trade volume, the use of renewable energy and keeping CO_2 emissions at a minimum level is of vital importance. For organizations or countries to ensure their sustainability, they need to constantly evaluate their efficiency and productivity. The study aims to conduct efficiency analyses using input and output variables from the Turkic Republics. However, data from the Republic of Turkmenistan was excluded because it was not available. For this reason, the effectiveness of CO2 emissions of Türkiye, Azerbaijan, Kazakhstan, Kyrgyzstan, and Uzbekistan is evaluated using the CRS DEA model. It is considered essential in terms of contributing to both organizations and policymakers.

The remainder of the study is organized as follows: The second section of the study includes a literature review. The third section includes the methods and data used in the study. The fourth section includes the findings of the study. The fifth section provides a general evaluation of the study.

2. LITERATURE

DEA method is widely used in many different areas such as technology, agriculture, banking, tourism, manufacturing systems, aviation, education and health (Emrouznejad and Yang, 2018; Çalışkan 2020; Menten et al., 2020; Ersoy, 2021; Ersoy and Aktaş, 2022; Xiao et al., 2023; Selamzade et al, 2023; Oukil et al., 2024; Antunes et al., 2024). As in many other sectors, studies are using the DEA method in the field of energy and logistics. Ervural et al. (2016) used the DEA method for renewable energy efficiency assessment of 81 different provinces of Türkiye. In the study, Total Renewable Energy Potential, Network Length, Total Installed Power of Renewable Energy, and Transformer Capacity were used as input variables, and Gross Energy Generation from Renewable Sources the number of Consumers were used as output variables. In the study, 81 provinces were ranked according to the results of output-oriented DEA analysis efficiency scores. A few potential improvement suggestions were presented for the provinces that were not efficient. Lu and Lu (2019) used the DEA method to examine the effects of CO_2 on the energy efficiency of 28 European countries between 2009 and 2013, selecting it as the undesirable output. In the study, labor force, real capital stock, and energy consumption were used as input variables, and the undesirable output of fossil fuel CO_2 emissions was used as the output variable. Güler et al. (2020) conducted the 2019 efficiency evaluation of 21 energy distribution companies operating in Türkiye using the DEA method. In the study, efficiency analyses were conducted using four different DEA models. The energy distribution companies that were found to be effective were ranked among themselves with the super efficiency DEA model and the most effective company was determined. Gan et al. (2021) used the DEA method to measure the green logistics effectiveness of 11 cities in Jiangxi Province, China between 2013 and 2019. In the study, capital, energy consumption, and employees were used as input variables, and demand scale, and added value of tertiary industry were used as output variables. Li et al. (2021) evaluated the carbon emission performance of 30 different regions in China between 2009 and 2015 using the fixed-sum undesirable outputs in the DEA method. In the study, capital stock, labor, and energy consumption were used as input variables, and gross domestic product and carbon dioxide emission was used as output variables. The study presented policy recommendations to improve carbon emission performance in different regions of China. Qin and Qi (2022) used the super-efficiency DEA model to determine the efficiency of the green logistics industry in Northwest China from 2010 to 2019. Four input and three output variables were used in the efficiency analysis. The study results provide some implications and suggestions for the high-quality development of a green logistics industry in Northwest China. Ersoy and Tehci (2023) conducted an efficiency evaluation of 15 companies operating in the energy sector in Türkiye using the DEA method. As a result of the efficiency analysis, four companies were found to be efficient, while the remaining 11 energy companies were found to be inefficient. Efficient companies were ranked among themselves according to the efficiency results of the super-efficiency DEA model, and the most efficient energy companies were identified. Lee et al. (2023) measured the efficiency of 27 logistics companies in Malaysia using the DEA method. Four input and four output variables were used in the study. As a result of the efficiency analysis, 15 companies were found to be effective, while the other 12 companies were found to be ineffective. Several potential improvement suggestions were made for the companies that were not found to be efficient. Yıldız (2023) evaluated the railway transportation efficiency of ten European countries and Türkiye determined according to the GNP rate. The research used data between the years 2011-2020. Data Envelopment Analysis - The Malmquist Index method was used to determine the efficiency changes depending on the years. The efficiency evaluations of the countries were made according to the total factor efficiency changes in the Malmquist Index values. Wang et al. (2023) used the DEA method and the Malmquist Index method to evaluate the CO_2 emission efficiency of the logistics sector in 9 coastal provinces of China between 2011 and 2020. In the study, Capital stock, Number of employees, and Energy consumption were used as input variables and Value added to the logistics industry, and CO_2 emissions were used as output variables. Junior et al. (2024) used the DEA method to evaluate the efficiency of CO_2 emissions in air transport for 21 countries between 2008 and 2019. In the study, the number of passengers, cargo transported, carrier departures, gross domestic product (GDP), and CO_2 emission from transportation undesirable were used as output variables, and several airports, and populations were used as input variables. According to the study results, 10 countries reached maximum efficiency in all years. Yağcı and Sözen (2024) used DEA and Malmquist Total Factor Efficiency index methods to analyze the energy efficiency and renewable energy efficiency of the European Union member countries and Türkiye between 2015 and 2017. According to the study results, the energy efficiency and renewable energy efficiency of the countries were determined, and the countries were ranked. When the literature was examined, it was determined that the super efficiency model was not used in the studies where CO2 emission efficiency was measured. This paper can contribute to the literature in this respect.

3. METHOD

3.1. Data Envelopment Analysis

Data Envelopment Analysis (DEA), developed by Farrell in 1957, is one of the most essential methods for measuring productivity in the production and service sectors (Farrell, 1957). Based on Farrell's work, DEA was developed by Charnes, Cooper, and Rhodes in 1978 with the assumption of constant returns to scale (CRS) (Charnes et al., 1978). In addition to the CRS method, which assumes that firms are efficient while on the production curve, DEA was developed by Banker, Charnes, and Cooper in 1984 with the assumption of variable returns to scale (VRS) while the search for the ideal method continued (Banker et al., 1984; Sevim et al. 2024). The basis of data envelopment analysis is based on the comparison of inputs and outputs of DMUs. DEA is accepted as a linear programming-based approach to evaluate the performance of DMUs (Cooper et al., 2011). DEA, which can express the efficiency values of decision-making units with multiple inputs and outputs as a single value, offers the opportunity to make an evaluation using multiple inputs and outputs such as cost, volume, and weight (Selamzade et al., 2023). The mathematical expression of DEA's efficiency measurement is the division of the weighted output total of the DMU by the weighted input total (Charnes et al., 1978; Yüksel, 2023).

$$\theta = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \tag{1}$$

To create a linear program in the output-oriented DEA calculation, the numerator of the Equation 1 is set equal to 1 (Charnes et al., 1978).

$$maximise \quad \theta_q \tag{2}$$

$$subject\ to \sum_{j=1}^{n} x_{ij}\lambda_j \leq x_{iq}, \qquad i = 1,2,\ldots,m, \tag{3}$$

$$\sum_{j=1}^{n} y_{kj}\lambda_j \geq \theta_q y_{kq}, \qquad k = 1,2,\ldots,r, \tag{4}$$

$$\lambda_j \geq 0, \qquad j = 1,2,\ldots,n. \tag{5}$$

The efficiency score obtained because of Equation 2 cannot be more than 1. DMUs with a value close to 1 are considered partially effective, and DMUs close to 0 are considered ineffective (Ersoy, 2021). When calculating DEA, first the units that provide maximum output with minimum input are determined from the compared DMUs, then the distances of the inefficient DMUs to the production limits (efficiency limits) are measured based on the weights obtained from the best alternative DMUs (Charnes et al., 1978). The efficiency score in DEA calculated with the CRS method can take a value between 0 and 1. In the following years, the Super Efficiency model was created by Seiford and Thrall (1990) to determine which of the effective DMUs is more effective by using DEA models. The effective DMUs in this model can take 1 or more values. Equations 6-8 are used to calculate the output-oriented CRS method Super Efficiency models (Seiford and Thrall, 1990).

$$Max\ \rho \tag{6}$$

$$subject\ to \sum_{\substack{j=1 \\ j\neq 0}}^{n} \lambda_j x_j \leq \rho x_0; \tag{7}$$

$$\sum_{\substack{j=1 \\ j\neq 0}}^{n} \lambda_j y_j \geq y_0;\ \rho,\ \lambda_j \geq 0;\ j \neq 0; \tag{8}$$

The input and output values of DMU_0 are shown as x_0 and y_0. As a result of the Super Efficiency analysis, it can be concluded that the company with a high score is better than a company with a lower super efficiency score, even if it has the same full efficiency score (1) as the others in the CRS analysis (Coelli et al., 1998).

3.2. Data of the Research

The input and output variables used in the study were obtained from the World Bank website (www.data.worldbank.org). In the efficiency analyses, the inverse of the carbon dioxide emission data ($1/CO_2$) was used as the output variable. The other two variables in Table 1 were used in the analyses as input variables.

Table 1. Variables of the research

Name	*Variables*	*Input / Output*
CO_2	Carbon dioxide emissions (Kt) ($1/CO_2$)	Output
GDP	Gross Domestic Product (constant 2015 USD)	Input
GEN	Green energy - Renewable energy consumption (% of total electricity production)	Input

The aim of the study was to determine the efficiency of Carbon dioxide emissions by taking into account the use of green energy - renewable energy consumption in the Turkic Republics. However, since the relevant data from the Republic of Turkmenistan could not be accessed, carbon emission activities of the Republics of Azerbaijan, Kazakhstan, Kyrgyzstan, Türkiye, and Uzbekistan were conducted.

4. RESULTS

4.1. CRS Model Analysis Results

The carbon footprint efficiency results calculated for the constant return to scale CRS method of the Data Envelopment Analysis of the Turkic Republics are presented in Table 2. CO_2 carbon dioxide emissions were used as outputs in the CRS analyses, GDP and Renewable energy consumption variables were used as inputs, and the years 1990-2020 were used as DMU in Table 2. In the CRS analysis Azerbaijan was effective in 1990, 1995, and 1996, Kazakhstan in 1998, 1999, Kyrgyzstan in 1995, 2001, and 2002, Türkiye in 1990, and Uzbekistan in 1995 and 2000. It was observed that the effectiveness scores of the Turkic Republic were generally not very high over the years. This situation is also seen from the effectiveness averages. As can be seen from Table 2, the efficiency score averages were 67.1% in Azerbaijan, 69.2% in Kazakhstan, 78.6% in Kyrgyzstan, 85.3% in Türkiye, and 74.6% in Uzbekistan. The highest and lowest effectiveness scores were in Azerbaijan. The years in which the closest scores to the efficiency score were obtained were 97.0% in Azerbaijan and Kazakhstan in 1997, 94.5% in Kyrgyzstan in 2005, 98.4% in Türkiye in 1991, and 96.9% in Uzbekistan in 1996. When the years in which the Turkic Republics received the lowest efficiency scores were examined, Azerbaijan had the lowest efficiency scores in 2010 (39.9%), Kazakhstan (48.4%), Uzbekistan in 2017 (46.4%), Kyrgyzstan (49.5%), and Türkiye in 2019 (60.2%).

Table 2. Carbon dioxide emission efficiency of countries

Year	*Azerbaijan*	*Kazakhstan*	*Kyrgyzstan*	*Türkiye*	*Uzbekistan*
1990	1	0.625	0.778	1	0.808
1991	0.942	0.658	0.763	0.984	0.830
1992	0.548	0.704	0.786	0.944	0.856
1993	0.471	0.712	0.860	0.926	0.805
1994	0.872	0.595	0.820	0.917	0.893
1995	1	0.764	1	0.921	1
1996	1	0.855	0.860	0.870	0.969
1997	0.970	0.970	0.870	0.848	0.954
1998	0.882	1	0.932	0.813	0.885
1999	0.843	1	0.887	0.860	0.785
2000	0.792	0.930	0.884	0.907	1
2001	0.954	0.838	1	0.947	0.932
2002	0.726	0.684	1	0.932	0.793
2003	0.551	0.628	0.826	0.950	0.710
2004	0.526	0.700	0.912	0.900	0.762
2005	0.440	0.591	0.945	0.941	0.634
2006	0.495	0.530	0.944	0.913	0.823
2007	0.415	0.576	0.886	0.941	0.808
2008	0.451	0.752	0.857	0.943	0.865
2009	0.507	0.748	0.844	0.897	0.612
2010	0.399	0.660	0.859	0.802	0.523
2011	0.437	0.618	0.704	0.840	0.729
2012	0.483	0.643	0.617	0.789	0.588
2013	0.519	0.694	0.599	0.770	0.670
2014	0.575	0.746	0.536	0.863	0.607
2015	0.538	0.637	0.582	0.720	0.525
2016	0.622	0.499	0.655	0.681	0.526
2017	0.635	0.484	0.602	0.712	0.464
2018	0.613	0.513	0.531	0.692	0.531
2019	0.669	0.553	0.495	0.602	0.486
2020	0.913	0.555	0.515	0.607	0.749
Average	0.671	0.692	0.786	0.853	0.746

The graph arranged with the efficiency results in Table 2 is shown in Figure 1. Although there was a partial increase in the efficiency scores of the countries between 1990 and 2000, there was a decrease in the efficiency scores after 2000. It was determined that there was an increase in the efficiency scores of Azerbaijan and Uzbekistan in 2020, while there was no change in the efficiency scores of other countries.

4.2. Super Efficiency CRS Model Analysis Results

The CRS model can determine efficient decision-making units, but it does not allow ranking of effective decision-making units. The super-efficiency CRS model is a method used to determine which of the efficient decision-making units is the most effective and to rank the effective decision-making units among themselves (Seiford and Thrall, 1990; Coelli et al., 1998; Ersoy, 2021; Selamzade et al., 2023). Table 3 shows the Super Efficiency scores calculated to determine which country is more efficient. As can be seen in Table 3, Azerbaijan reached the highest efficiency level in 1990. Kazakhstan had the highest efficiency score in 1999. Kyrgyzstan, on the other hand, achieved the highest score in 1990.

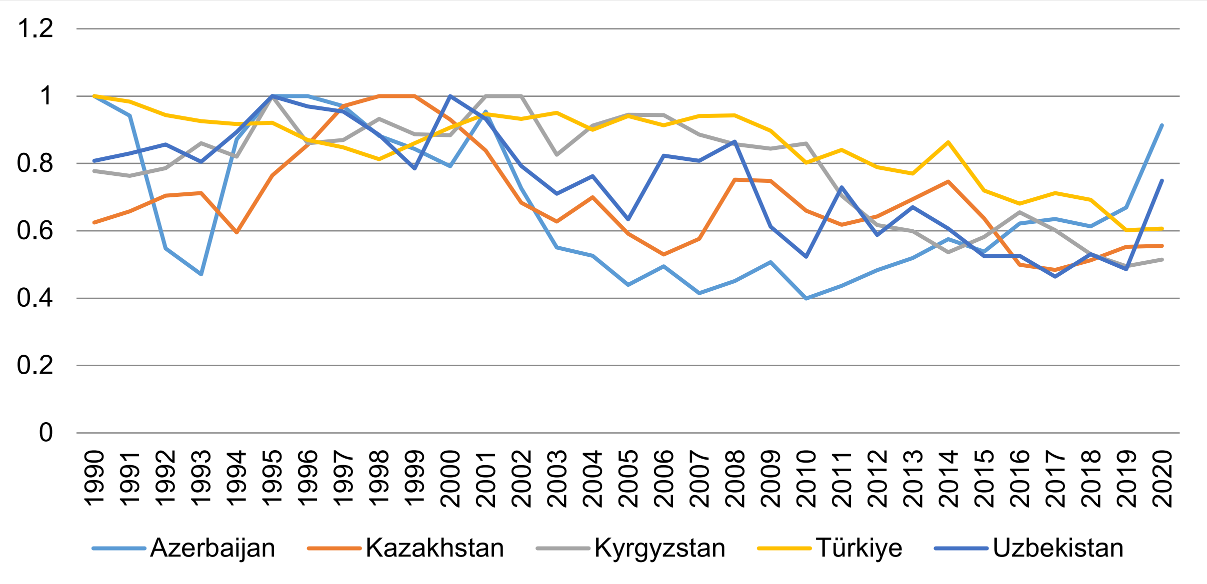

Figure1. Carbon dioxide emission efficiency of countries

Table 3. Super efficiency scores

Year	*Azerbaijan*	*Year*	*Kazakhstan*	*Year*	*Kyrgyzstan*	*Year*	*Türkiye*	*Year*	*Uzbekistan*
1990	1.082	1999	1.070	1995	1.193	1990	1.040	2000	1.100
1996	1.069	1998	1.049	2001	1.053			1995	1.070
1995	1.051			2002	1.015				

It was determined that Türkiye was super-efficient in 1990. Uzbekistan reached highest efficiency score in 1990. CO_2 Emission Reduction Proposal for Countries' Inefficient Years can be seen in Table 4.

Table 4. CO_2 emission reduction proposal for countries' inefficient years

Country	*Year*	*Efficiency Score*	*%*
Azerbaijan	1997	0.970	-2.97
	2010	0.399	-60.13
Kazakhstan	1997	0.971	-2.92
	2017	0.484	-51.57
Kyrgyzstan	2005	0.945	-5.54
	2019	0.495	-50.45
Türkiye	1991	0.984	-1.62
	2019	0.602	-39.75
Uzbekistan	1996	0.969	-3.1
	2017	0.464	-53.57

5. CONCLUSION

Today, with increasing environmental concerns and industrial developments, it becomes clear that environmental problems should be evaluated together with supply chain management, and thus more crucial should be given to green supply chain management. Green supply chain management includes activities such as green production, green logistics, green marketing, and green energy (Tatar and Özer, 2017). Since any disruption in logistics activities in the supply chain will cause an increase in carbon emissions, managers are advised to look for green alternatives in logistics activities (Wiedmann et al., 2010; Amiruddin et al., 2021; Turgut and Budak, 2022). The current study aims to analyze the carbon emission activities of the Turkic Republics using the DEA method. According to the CRS DEA analysis results, effective decision-making units were determined. Efficient decision-making units were ranked using the super-efficiency CRS DEA model. Several potential improvement suggestions were presented for the decision-making units that were not effective to become effective. According to the potential improvement suggestions made because of the efficiency analyses, it is possible to say that energy production and consumption have a key role in the development of countries and that more essentials should be given to green energy production to keep CO_2 emissions under control.

It is possible to say that increasing the use of green energy in logistics operations reduces carbon emissions. This situation is expected to have a positive effect on reducing carbon emissions in the entire supply chain management indirectly. According to the results of this study, it is consistent with other studies in the literature that more importance should be given to the concepts of green energy and green logistics to reduce CO_2 emissions (He et al., 2017; Herold and Lee, 2017; Tatar and Özer, 2017; Jiang et al., 2020; Amiruddin et al., 2021; Turgut and Budak, 2022). However, since the research results are directly related to the input and output variables used in the analysis, changes in the variables can affect the results. In fact, in this study, efficiency analyses were performed using CRS DEA method. When evaluated from this perspective, it was seen that the efficiency results obtained with DEA were relative.

The current study has some limitations. One of the limitations of the study is that only data from 5 Turkic Republics can be used in the study. Another essential limitation is that DEA analyses were performed with only 1 output variable. Another limitation is that the analyses covered the years 1990-2020. In future studies, efficiency measurements can be applied using different input and output variables. In addition to the DEA method, studies can be conducted using multi-criteria decision-making methods or different methods.

REFERENCES

Amiruddin, S. Z., Hishamuddin, H., Darom, N.A. and Naimin, H.H. (2021). “A Case Study of Carbon Emissions from Logistic Activities During Supply Chain Disruptions”, *Jurnal Kejuruteraan*, 33(2), 221-228. https://doi.org/10.17576/jkukm-2021-33(2)-07

Antunes, J., Hadi-Vencheh, A., Jamshidi, A., Tan, Y., and Wanke, P. (2024). “Cost Efficiency of Chinese Banks: Evidence from DEA and MLP-SSRP Analysis”, *Expert Systems with Applications*, 237. https://doi.org/10.1016/j.eswa.2023.121432

Banker, R.D., Charnes, A. and Cooper, W.W. (1984). “Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis”, *Management Science*, 30(9), 1078-1092. https://doi.org/10.1287/mnsc.30.9.1078

Çalışkan, H. (2020). “Evaluation of the Productivity levels of Public Hospital Unions by Data Envelopment Analysis”, *Journal of Productivity*, 2020(2), 157-178.

Charnes, A., Cooper, W. and Rhodes, E. (1978). “Measuring the Efficiency of Decision Making Units”, *European Journal of Operational Research*, 2(6), 429-444. https://doi.org/10.1016/0377-2217(78)90138-8

Chukurna, O., Nitsenko, V., Tyukhtenko, N., Lomonosova, O., Zhartay, Z. and Dobrovolskyi, V. (2022). “Substantiation of the Green Approach in the Formation of a Sustainable System of Ecological Logistics”, *Scientific Bulletin of National Mining University*, (1), 76-82. https://doi.org/10.33271/nvngu/2022-1/076

Coelli, T.J., Rao, D.S.P., O’Donnel, C.J. and Battese, G.E. (1998). “An Introduction to Efficiency and Productivity Analysis”, 2nd Ed. Springer, New York

Cooper, W.W., Seiford, L.M. and Zhu J. (2011). “Handbook on Data Envelopment Analysis”, 2nd Ed. Springer, New York.

Çoban, O. (2015). “Relationship Between Renewable Energy Consumption and Carbon Emissions: The case of Turkey”, *Erciyes University Journal of Social Sciences Institute*, 1(38), 195-208.

Dekker, R., Bloemhof, J. and Mallidis, I. (2012). “Operations Research for Green Logistics – An Overview of Aspects, Issues, Contributions and Challenges”, *European Journal of Operational Research*, 29(3), 671-679. https://doi.org/10.1016/j.ejor.2011.11.010

Emrouznejad, A. and Yang, G-L. (2018). “A Survey and Analysis of the First 40 Years of Scholarly Literature in DEA: 1978–2016”, *Socio-Economic Planning Sciences*, 61, 4-8. https://doi.org/10.1016/j.seps.2017.01.008

Ersoy, Y. and Aktaş, A. (2022). “Health System Efficiency of OECD Countries with Data Envelopment Analysis”, *Problemy Zarządzania - Management Issues*, 20(4), 90-109. https://doi.org/10.7172/1644-9584.98.4

Ersoy, Y. and Tehci, A. (2023).” Efficiency Evaluation of Energy Companies with Data Envelopment Analysis”, *The Journal of International Scientific Researches*, 8(3), 360-366. https://doi.org/10.23834/isrjournal.1331147

Ersoy, Y. (2021). “Performance Evaluation in Distance Education by Using Data Envelopment Analysis (DEA) and TOPSIS Methods”, *Arabian Journal of Science and Engineering*, 46, 1803-1817. https://doi.org/10.1007/s13369-020-05087-0

Ervural, B.C., Ervural, B. and Zaim. S. (2016). “Energy Efficiency Evaluation of Provinces in Turkey Using Data Envelopment Analysis”, *Procedia - Social and Behavioral Sciences*, 235, 139-148. https://doi.org/10.1016/j.sbspro.2016.11.009

Farrell, M.J. (1957). “The Measurement of Productive Efficiency”, *Journal of the Royal Statistical Society: Series A (General)*, 120(3): 253-281. https://doi.org/10.2307/2343100

Gan, W., Yao, W. and Huang, S. (2022). “Evaluation of Green Logistics Efficiency in Jiangxi Province Based on Three-Stage DEA from the Perspective of High-Quality Development”, *Sustainability*, 14(2), 1-19. https://doi.org/10.3390/su14020797

Güler, E., Kandemir, S.Y. and Açıkkalp, E. (2020). “Evaluation of the Efficiencies of the Energy Distribution Companies in Turkey with DEA”, *BSEU Journal of Science*, 7(1), 66-79. https://doi.org/10.35193/bseufbd.683652

He, Z., Chen, P., Liu, H. and Guo, Z. (2017). “Performance Measurement System and Strategies for Developing Low-Carbon Logistics: A Case Study in China”, *Journal of Cleaner Production*, 156, 395-405. https://doi.org/10.1016/j.jclepro.2017.04.071

Herold, D.M. and Lee, K-H. (2017). “Carbon Management in the Logistics and Transportation Sector: An Overview and New Research Directions”, *Carbon Management*, 8:1, 79-97. https://doi.org/10.1080/17583004.2017.1283923

Jiang, X., Ma, J., Zhu, H., Guo, X. and Huang, Z. (2020). “Evaluating the Carbon Emissions Efficiency of the Logistics Industry Based on a Super-SBM Model and the Malmquist Index from a Strong Transportation Strategy Perspective in China”, *International Journal of Environmental Research and Public Health*, 17(22), 8459. https://doi.org/10.3390/ijerph17228459

Junior, Q.H. da S., Celestino, M.A. de S., de Souza, C.F.F., Falcao, V.A. and Camioto, F. de C. (2024). “CO_2 Emissions in Air Transport: A Comparative Study Using Data Envelopment Analysis”, *Transportation Research Record*, 2678(5), 872-883. https://doi.org/10.1177/03611981231193407

Larina, I.V., Larin, A.N., Kiriliuk, O. and Ingaldi, M. (2021). “Green Logistics-Modern Transportation Process Technology”, *Production Engineering Archives*, 27(3), 184-190. http://dx.doi.org/10.30657/pea.2021.27.24

Lee, P.F., Lam, W.S. and Lam, W.H. (2023). “Performance Evaluation of the Efficiency of Logistics Companies with Data Envelopment Analysis Model”, *Mathematics*, 11(3), 718. https://doi.org/10.3390/math11030718

Li, Y., Hou, W., Zhu, W., Li, F. and Liang, L. (2021). “Provincial Carbon Emission Performance Analysis in China Based on a Malmquist Data Envelopment Analysis Approach With Fixed Sum Undesirable Outputs”, *Annals of Operations Research*, 233-261. https://doi.org/10.1007/s10479-021-04062-8

Lu, C-C. and Lu, L-C. (2019). “Evaluating the Energy Efficiency of European Union Countries: The Dynamic Data Envelopment Analysis”, *Energy & Environment*, 30(1), 27-43. https://doi.org/10.1177/0958305X18787257

Lu, Y. and Li, S. (2023).” Green Transportation Model in Logistics Considering The Carbon Emissions Costs Based on İmproved Grey Wolf Algorithm”, *Sustainability*, 15(14), 11090. https://doi.org/10.3390/su151411090

Menten, C., Çekiç, B. and Atıcı, K.B. (2020). “The Product- Based Efficiency Evaluation of Turkish Agricultural Sector”, *Journal of Productivity*, 2020(1), 117-141.

Ministry of Foreign Affairs, MFA. (2024a). “Azerbaycan'ın Ekonomisi”, https://www.mfa.gov.tr/azerbaycan-ekonomisi.tr.mfa, (Accessed: 21.07.2024).

Ministry of Foreign Affairs, MFA. (2024b). “Kazakistan Cumhuriyeti’nin Ekonomisi”, https://www.mfa.gov.tr/kazakistan-cumhuriyeti-ekonomisi.tr.mfa, (Accessed: 21.07.2024).

Ministry of Foreign Affairs, MFA. (2024c). “Kırgızistan Cumhuriyeti’nin Ekonomisi”, https://www.mfa.gov.tr/kirgizistan-cumhuriyeti-ekonomik-iliskileri.tr.mfa, (Accessed: 21.07.2024).

Ministry of Foreign Affairs, MFA. (2024d). “Özbekistan Cumhuriyeti’nin Ekonomisi”, https://www.mfa.gov.tr/ozbekistan-cumhuriyeti-ekonomisi.tr.mfa, (Accessed: 21.07.2024).

Ministry of Trade (2024) “Statistics”, https://www.trade.gov.tr/statistics, (Accessed: 20.06.2024).

Oukil, A., Kennedy, R.E., Al-Hajri, A. and Soltani, A.A. (2024). “Unveiling the Potential of Hotel Mergers: A Hybrid DEA Approach for Optimizing Sector-Wide Performance in the Hospitality Industry”, *International Journal of Hospitality Management*, 116. https://doi.org/10.1016/j.ijhm.2023.103620

Qin, W. and Qi, X. (2022). “Evaluation of Green Logistics Efficiency in Northwest China”, *Sustainability*, 14(11), 6848. https://doi.org/10.3390/su14116848

Seiford, L.M. and Thrall, R.M. (1990). “Recent Developments in DEA: the Mathematical Programming Appoach to Frontier Analysis”, *Journal of Econometrics*, 4, 7-38. https://doi.org/10.1016/0304-4076(90)90045-U

Selamzade, F., Ersoy, Y., Ozdemir, Y. and Celik, M.Y. (2023). “Health Efficiency Measurement of OECD Countries Against the COVID-19 Pandemic by Using DEA and MCDM Methods”, *Arabian Journal for Science and Engineering*, 48(11), 15695-15712. https://doi.org/10.1007/s13369-023-08114-y

Sevim F., Şenol, O. and Akbulut F. (2024). “Evaluation of the Efficiency of Long-Term Care Services in OECD Countries by DEA Method”, *Journal of Midwifery and Health Sciences*, 7(2), 376-387

Tatar, V. and Özer, M.B. (2017). “The Role of Logistics and Transport in Reducing Supply Chain Carbon Emissions”, *Journal of Social and Humanities Sciences Research*, 4(11), 631-637. https://doi.org/10.26450/jshsr.102

TÜBA (2022). “TÜBA Report on the Role of Artificial Intelligence in Energy”, https://www.tuba.gov.tr/tr/yayinlar/suresiz-yayinlar/raporlar/tuba-enerjide-yapay-zeknin-rolu-raporu, (Accessed: 20.06.2024).

Turgut, A. and Budak, T. (2022). “Carbon Footprint of Logistics and Transportation: A Systematic Literature Review”, *Urban Academy*, 15(2), 91-930. https://doi.org/10.35674/kent.1071319

Ulewicz, R., Siwiec, D., Pacana, A., Tutak, M. and Brodny, J. (2021). “Multi-Criteria Method for the Selection of Renewable Energy Sources in the Polish Industrial Sector”, *Energies*, 14(9), 2386. https://doi.org/10.3390/en14092386

Wang, H., Liu, X. and Liang, Y. (2023). “Measurement of CO_2 Emissions Efficiency and Analysis of Influencing Factors of the Logistics Industry in Nine Coastal Provinces of China”, *Sustainability*, 15(19), 1-21. https://doi.org/10.3390/su151914423

Wiedmann, T., Wood, R., Minx, J.C., Lenzen, M., Guan, D. and Harris, R. (2010). “A Carbon Footprint Time Series of the UK–Results from a Multi-Region Input–Output Model”, *Economic Systems Research*, 22(1), 19-42. https://doi.org/10.1080/09535311003612591

Worldbank (2024). “Data”, https://data.worldbank.org/, (Accessed: 20.06.2024).

Xiao, K., Ullah, W., Fu, J. and Zhang, X. (2023). “Poverty Alleviation Efficiency of Tourism and Its Spatiotemporal Differentiation in Jiangxi Province of China Based on the DEA Model”, *Sage Open*, 13(2). https://doi.org/10.1177/21582440231168835

Yağcı, B.E. and Sözen, A. (2024). “Turkey’s Energy Efficiency Activity Analysis”, *Journal of Polytechnic*, https://doi.org/10.2339/politeknik.859790

Yıldız, R. (2023). " Performance Evaluation in Railway Transport: The Case of Europe and Türkiye", Journal of Productivity, 57(4), 609-622. https://doi.org/10.51551/verimlilik.1232150

Yüce, M. (2022). "Orta Asya Türk Cumhuriyetleri ve Türkiye ile İlişkiler", https://www.setav.org/assets/uploads/2022/03/R195.pdf, SETA, İstanbul, (Accessed: 20.07.2024).

Yüksel, O. (2023). "Efficiency in Medical Imaging Techniques in Hospitals According to Sectors", *Munzur Unıversıty Journal of Social Sciences,* 12(2), 133-152.

Zadmirzaei, M., Hasanzadeh, F., Susaeta, A. and Gutiérrez, E. (2024). "A Novel Integrated Fuzzy DEA–Artificial Intelligence Approach for Assessing Environmental Efficiency and Predicting CO2 Emissions", *Soft Computing*, 28(1), 565-591. https://doi.org/10.1007/s00500-023-08300-y

VERİMLİLİK DERGİSİ
JOURNAL OF PRODUCTIVITY

Performance Evaluation of Turkish Ports: Integrated Fuzzy Entropy- Fuzzy MARCOS Analysis

Özlem Karadağ Albayrak[1]

ABSTRACT
Purpose: The aim of this study is to propose the Fuzzy Entropy based Fuzzy MARCOS method to solve the Multi Criteria Decision Making (MCDM) problem, which involves analyzing the performance of Turkish ports according to quantitative evaluation criteria.
Methodology: The uncertainty of quantitative criteria is based on the different values they take at different time periods. To overcome this problem, in this study, the importance levels of the criteria were determined by the Fuzzy Entropy method. Then, 11 port alternatives with a share of over 1% in transportation in Turkish ports were ranked according to their performance using the Fuzzy Measurement of Alternatives and Ranking to Compromise Solution (MARCOS) method.
Findings: According to the analysis results, the most important evaluation criterion used in the performance evaluation of container ports, that is, the criterion with the highest weight, is the "port area" criterion. The port with the highest performance value among the ports is Kocaeli port. This method can provide a more accurate evaluation of the performance level of ports and its use in the planning and effective use of port investments.
Originality: This research fills the gap in the literature in three ways: (1) Evaluatee the application of triangular fuzzy numbers to the panel data, which will provide effective inferences about the performanse level of the selected ports, (2) Evaluated a weighting approach using Entropy method that takes into account the distances of triangular fuzzy numbers consisting of real numbers instead of linguistic expressions, (3) An Entropy-based MARCOS method is proposed for solving the Multi-Criteria Decision Making (MCDM) problem involving the performanse analysis of Turkish ports.
Keywords: Ports, Maritime Transport, Fuzzy ENTROPY, Fuzzy MARCOS.
JEL Codes: C61, D81, L91.

Türk Limanlarının Performanslarının Değerlendirmesi: Entegre Bulanık Entropi-Bulanık MARCOS Analizi

ÖZET
Amaç: Bu çalışmanın amacı, Türk limanlarının nicel değerlendirme kriterlerine göre performanslarının analiz edilmesini içeren Çok Kriterli Karar Verme (ÇKKV) probleminin çözümü için Bulanık Entropi tabanlı Bulanık MARCOS yöntemini önermektir.
Yöntem: Nicel kriterlerin belirsizliği, farklı zaman dilimlerinde aldıkları farklı değerlere dayanmaktadır. Bu sorunu aşmak için, bu çalışmada, kriterlerin önem seviyeleri Bulanık Entropi yöntemi ile belirlenmiştir. Daha sonra, Türk limanlarında taşımacılıkta %1'in üzerinde paya sahip 11 liman alternatifi, Alternatiflerin Bulanık Ölçümü ve Uzlaşmaya Göre Sıralama (MARCOS) yöntemi kullanılarak performanslarına göre sıralanmıştır.
Bulgular: Analiz sonuçlarına göre, konteyner limanlarının performans değerlendirmesinde kullanılan değerlendirme kriterlerinden en önemlisi yani en yüksek ağırlığa sahip olan kriter liman alanı kriteridir. Limanlar arasında en yüksek performans değerine sahip liman limanın Kocaeli limanıdır. Bu yöntem limanların performans düzeyinin daha doğru değerlendirilmesini ve liman yatırımlarının planlanmasında ve etkin kullanımında kullanılmasını sağlayabilir.
Özgünlük: Bu araştırma literatürdeki boşluğu üç açıdan doldurmaktadır: (1) Seçilen limanların verimlilik düzeyi hakkında etkili çıkarımlar sağlayacak olan üçgen bulanık sayıların panel verilerine uygulanması değerlendirilmiş, (2) Dilsel ifadeler yerine gerçek sayılardan oluşan üçgen bulanık sayıların uzaklıklarını hesaba katan Entropi yöntemini kullanan bir ağırlıklandırma yaklaşımını değerlendirilmiş, (3) Türk limanlarının performans analizini içeren Çok Kriterli Karar Verme (ÇKKV) problemini çözmek için Entropi tabanlı bir MARCOS yöntemi önerilmiştir.
Anahtar Sözcükler: Limanlar, Denizyolu Taşımacılığı, Bulanık ENTROPİ, Bulanık MARCOS.
JEL Kodları: C61, D81, L91.

[1] Kafkas University, Faculty of Economics and Administrative Sciences, Department of International Trade and Logistics, Kars, Türkiye

Corresponding Author: Özlem Karadağ Albayrak, ozlemkaradagalbayrak@gmail.com
DOI: 10.51551/verimlilik.1532908
Research Article | Submitted: 13.08.2024 | Accepted: 11.12.2024
Cite: Karadağ Albayrak, Ö. (2025). "Performance Evaluation of Turkish Ports: Integrated Fuzzy Entropy- Fuzzy MARCOS Analysis", *Verimlilik Dergisi,* Productivity for Logistics (SI), 149-166.

1. INTRODUCTION

Maritime transportation is an economically, environmentally, and socially advantageous alternative for both cargo and passenger transportation. In parallel with global developments, there is a desire to switch from road transportation to maritime transportation within the concept of sustainable transportation. Ports are one of the most important actors in the global supply chain and world trade. Due to the great economic benefits that ports bring to port cities for regional development, there is a global economic transfer tendency towards port cities (Ferrari et al., 2010). Almost 90% of international transportation in the world is carried out by maritime transportation mode. Türkiye has a large and strategically important maritime area in the Black Sea, Western Europe, Middle East and North Africa regions, with a 8,333 km coastline providing direct sea connections to various countries in geographical and geopolitical areas. In terms of the value of the goods transported, maritime transportation has the largest share in both imports and exports in the last 10 years. While the highest share of maritime transportation in imports was 69.14% in 2015, this share was 65.74% in 2022 between 2012-2022. The highest share of maritime transportation in export shipments was 63.31% in 2018 from 2012 to 2022, and this share was 59.56% in 2022 (UTİKAD, 2022: 133).

Türkiye has many advantages on the way to becoming a logistics base in world trade. These advantages include the ability to use different modes simultaneously, the fact that it has coasts on the Mediterranean, Black and Aegean Seas for maritime transportation, and that the Sea of Marmara is an inland sea. In addition, the Baku-Tbilisi-Kars (BTK) Railway Line can be shown as the capacity to transport directly from Asia to Europe or with different mode connections. The extent to which these advantages of Turkiye can be used can be evaluated with the logistics performance index and different indices.

The Logistics Performance Index (LPI) report, which was first published in 2007 and prepared by the "Global Trade and Regional Integration Unit" of the World Bank, aims to rank countries in the world according to their logistics performance. The evaluation criteria of the logistics performance index are customs, infrastructure, international transportation, competence and quality, timing and tracking/monitoring. Türkiye ranked 47th in the LPI prepared in 2018, and 42nd in the LPI 2023, which includes 139 countries (WB, 2024). International transportation: Turkiye ranked 53rd in 2018 and rose to 26th place in 2023. One of the performance indicator indices of maritime transportation is the Regular Liner Shipping Connectivity Index (LSCI). This index measures the level of integration in regular liner shipping. Türkiye is among the countries in the 50-70 index range as a country. Different LSCI index values of Turkish ports are presented in Figure 1.

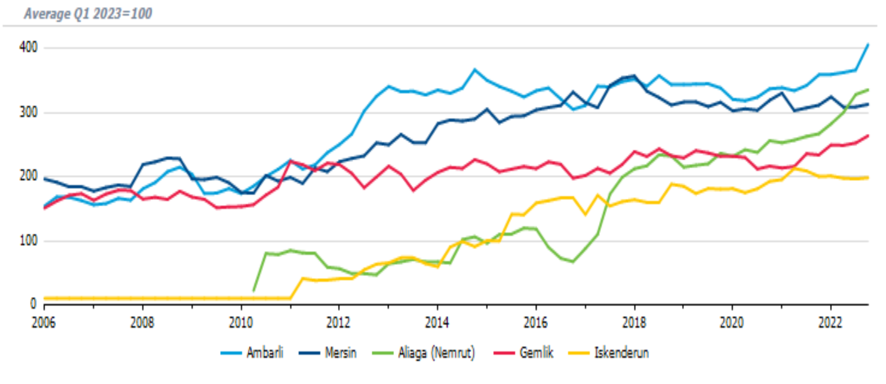

Figure 1. Port liner shipping connectivity index- Top 5 ports in 2022 (UNCTAD, 2024)

Approximately 60% of the active time in international trade is spent at sea, and the majority of delays occur at the departure or arrival points of containers (ports, airports) (Boztepe, 2023). According to the 2023 report of the Turkish Port Operators Association, Türkiye's loading and unloading averages are 54 and 30 tons per minute, while the average ship waiting times for loading and unloading are 36 and 37 hours. In addition to the inability of countries to use their existing capacity, global developments are affecting the activities of Turkish ports. There have been significant decreases in container handling in the Black Sea due to the Russia-Ukraine tension. When the data for the first 9 months of 2022 is examined, it is seen that there is a decrease of 80% in Ukrainian ports and a decrease of 11% in Russian ports in the Black Sea. In total, container handling in the Black Sea decreased by 25% (TLID, 2023: 79).

The performanse measure is directly related to the productivity measure. The idea behind the similar use of both concepts is that a firm's performance improves the more efficient and productive it is (Gonzalez and Trujillo, 2009). Port efficiency has a key role in determining transportation costs and hence international trade between countries (Clark et al., 2004). The panel set data used in this study are panel data series of port data. Since panel data sets contain different values at different times, it covers more than one data set.

This feature allows time differences in variables to be included in the model under study. For this reason, the variables are expressed in the form of triangular fuzzy numbers by taking the maximum value, minimum value and average value in the time interval in the panel data set.

Cargo ports are places that provide cargo transshipment services to and from ships (as opposed to producing a physical product). This capability is enhanced if ports are technically and cost efficient (Chang and Talley, 2019). Ports are important areas in international trade as areas where cargo is stored for a certain period of time with connections to different transportation modes and where value-added logistics services are provided (Şişlioğlu, 2021). Maritime transportation is one of the most important components of domestic and foreign trade in the world. The high increase in the demand for maritime transportation, especially container transportation, in recent years suggests that companies should choose the most suitable container port to integrate their transportation networks (Onut et al., 2011).

In the mid-90s, the performanse literature, already applied to a large number of industries, was introduced for the port sector. The diversity of approaches applied reflects the lack of consensus in identifying the method that best describes the complex reality of this sector (Gonzalez and Trujillo, 2009). Port evaluation and selection problems can be considered as multi-criteria decision problems due to the competing interests of the evaluation criteria. Each criterion has different levels of importance. These importance levels are expressed as criteria weights. Different quantitative and qualitative methods can be used to determine these weights. If the subjective evaluation of the users is to be made directly, expert opinion is used. However, quantitative methods are preferred for objective evaluation. In this study, an objective evaluation was aimed according to the existing data sets and Fuzzy Entropy method was used to determine the criteria weights. Shannon entropy, also known as information entropy, is used to describe the uncertainty in the occurrence of each possible event in an information source (Nemzer, 2017). According to Shannon, information entropy is negatively related to the regularity of the system and its value decreases as the regularity of the system increases. That is, a more ordered system has lower information entropy; a more disordered system has higher information entropy. In an MCDM problem, the smaller the information entropy of a criterion, the greater its influence on the overall evaluation and the more weight will be given to it (Li et al., 2024).

The selection of criteria weights as well as the ranking and evaluation of alternatives are complex decision problems. Making decisions based solely on intuition and experience can lead to wrong decisions and unexpected costs. Multi-criteria decision making (MCDM) approaches have been proposed in the literature to overcome this problem (Kadaifci et al., 2019). There are many different MCDM methods used to solve ranking or selection problems among alternatives. In this study, the MARCOS method presented by Stević et al. (2020) was used to rank the performanse of ports. The MARCOS method proposes a feasible compromise solution that is closest to the ideal. It is also flexible in analyzing expert preferences regardless of the type of scale (Büyüközkan, 2021). This method is used in its fuzzy form and integrated with the fuzzy Entropy method.

The contribution from this research are listed as follows;

(1) Evaluate the application of triangular fuzzy numbers to the panel data, which will provide effective inferences about the performanse level of the selected ports.

(2) Evaluation of a weighting approach using the Entropy method, which evaluates by taking into account the distance between triangular fuzzy numbers, that is, the values in the data set, which are composed of real numbers instead of linguistic expressions, that is, whether they are high or low compared to each other.

(3) An Entropy-based MARCOS method is proposed for solving the Multi-Criteria Decision Making (MCDM) problem involving the performans**e** analysis of Turkish ports.

The organization of the study is as follows: Section 2 presents preliminary information. Section 3 describes the methods used. In Section 4, our proposed method is applied and the performanse ranking of the ports is obtained. Section 5 presents and discusses the results obtained.

2. LITERATURE REVIEW

There are different studies in the literature for the evaluation of ports. Baysal et al. (2004) evaluated the efficiency and perfromanse analysis of Turkish ports with data envelopment analysis method. Onut et al. (2011) used the FANP method to solve the optimal port search problem of a company in the Marmara Region that has quality problems. Ateş and Esmer (2014) evaluated the efficiency of Turkish container ports using Data Envelopment Analysis (DEA) and Free Disposable Envelope Model (FDH) models. Ateş et al. (2013) used Data Envelopment Analysis (DEA) to determine the relative efficiencies of 9 container terminals (Novorossisk, Odesa, Varna, Burgas, Batumi, Poti, Ilyichevsk, Constanza and Trabzon) operating in the Black Sea region (Türkiye, Georgia, Ukraine, Bulgaria, Romania and Romania) within the framework of theTransport Corridor Europe-Caucasus-Asia (TRACECA) program in 2011. Akyürek (2017) analyzed the efficiency of Black Sea ports. Akgül (2018) analyzed the market structure and competitiveness of cruise ports in Türkiye. Balık (2023) In this study, the share of cargo handled in Antalya Port in total cargo handled in Türkiye and comparative cargo analysis with Mersin and Izmir ports, which are the two closest commercial ports to the east and west. Öztemiz and Vatansever (2023) investigated the relationship between container port volume and foreign trade in container port projects with econometric analysis. Özgüven and Güngör (2023) made an evaluation of blockchain technology in terms of Turkish ports.

Feng (2011) compared the performance of Western European and East Asian ports. Rudjanakanoknas and Suksirivoraboot (2012) analyzed the trade facilitation of four ports in Thailand. Cabral and Sousa (2014) This paper compared the competitiveness of Brazilian container ports handling containers in 2009. Gamassa and Chen (2017) compared port efficiency between East and West African ports using Data Envelopment Analyses. Garcia-Alonso et al. (2019) evaluated the competition between three major container ports in Spain, namely Barcelona, Bilbao and Valencia, using Geographic Information System (GIS). Ding et al. (2019) used the Analytic Hierarchy Process (AHP) method and the Decision Making Trial and Evaluation Laboratory (DEMATEL) technique to evaluate the key determinants of attractiveness and their cause/effect relationships for container ports in Taiwan. Andriotti et al. (2021) analyzed Brazilian public ports and port pricing figures, taking into account the Rio de Janeiro Port Authority and its two main managed ports (Rio de Janeiro and Itaguaí) in order to assess the need for adequacy and self-sustainability in ports. Lorencic et al. (2022) conducted a performance evaluation of four Mediterranean cruise ports, namely Barcelona, Piraeus, Civitavecchia and Marseille, using the MCDM approach. Wang et al. (2024) solved the problem of selecting sustainable food suppliers using the Pythagorean fuzzy CRITIC-MARCOS method.

Stević et al. (2020) introduced the idea of measuring and ranking alternatives according to the consensus solution (MARCOS) method, which is based on the distance of alternatives from reference points according to the criteria considered and their total score reflected by a utility function. Ali (2022) listed the advantages of the MARCOS method as follows: the consideration of reference points over the ideal and non-ideal solution at the beginning of model formation, the further determination of the degree of utility of both sets of solutions, the proposal of a new way of determining the utility functions and their sum, and the ability to consider a large number of criteria and alternatives. Wang et al. (2023) developed a Fermatean fuzzy MARCOS method based on expectation theory to analyze the risk of construction operations. Later, different methods were integrated into the MARCOS method.

Among these studies, no study was found that took into account the size differences between the members of the data sets. Fuzzy logic is generally used to convert qualitative evaluations of expert opinions into quantitative ones. However, in this study, existing quantitative panel data sets were converted into fuzzy form and used for evaluation.

3. METHODOLOGY

In the study, the evaluation criteria, which are the indicators of the performanse analysis of the ports, were weighted by Fuzzy Entropy method. Then, Fuzzy MARCOS method was applied for performanse ranking. The steps taken for the model recommendation are presented in Figure 2.

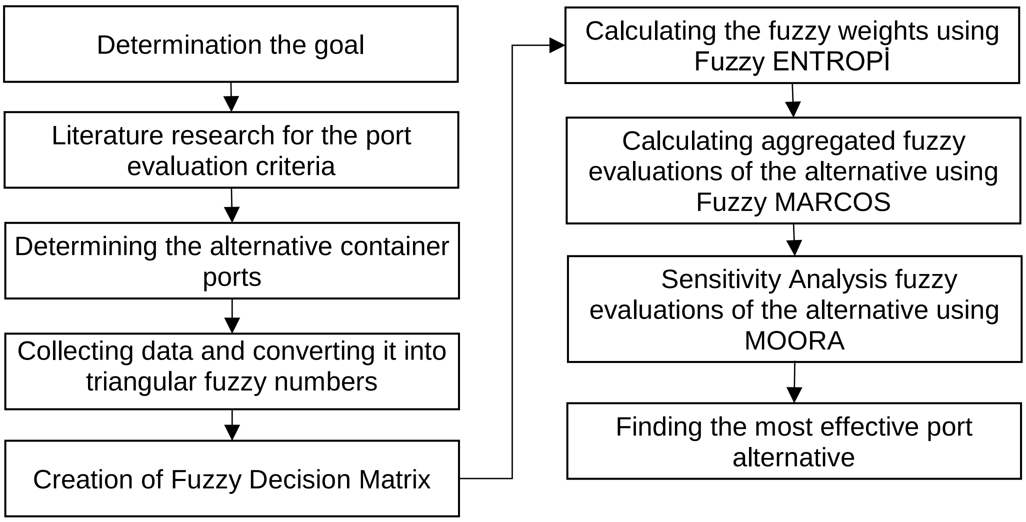

Figure 2. The proposed model for determining the performanse of Turkish ports

In the study, the evaluation criteria presented in Table 1 were used as the performanse indicators of the ports.

Table 1. List of research criteria

Criterion No	*Criteria Description*	*Abbreviation*	*Unit*	*Papers Using Criteria*
C1	Container handling operations carried out in our ports on the basis of port authorities-Import	KİTH	TEU/TEUs	Onut (2011), Balık (2023), Öztemiz and Vatansever (2023), Gamassa and Chen (2017), Ateş et al. (2013), Ateş and Esmer (2014)
C2	Container handling operations carried out in our ports on the basis of port authorities- Export	KİHR	TEU/TEUs	Onut (2011), Balık (2023), Öztemiz and Vatansever (2023), Gamassa and Chen (2017), Ateş et al. (2013), Ateş and Esmer (2014)
C3	Cargo handling carried out in our ports on the basis of port authorities-İmport	YİTR	Ton	Onut (2011), Gamassa and Chen (2017), Baysal et al. (2004)
C4	Cargo handling carried out in our ports on the basis of port authorities-Export	YİHR	Ton	Onut (2011), Gamassa and Chen (2017)
C5	Number of ships calling at our ports based on port authorities	GS	Adet	Poitras et al. (1996)
C6	Gross Ton ship calling at our ports based on port authorities	GGT	Gros Ton	Şişlioğlu (2021),
C7	Port Area	LA	m^2	Ateş et al (2013), Ateş and Esmer (2014), Kadaifci et al. (2019).
C8	Container Dock/Pier Length	LU	m	Feng et al (2011), Gamassa and Chen (2017), Ateş et al. (2013), Ateş and Esmer (2014)
C9	Draft	D	m	Ateş et al (2013), Ateş and Esmer (2014)

A set of crips numbers (sharp numbers) is a collection of $x \in X$ elements or objects that can be finite, countable or extremely variable (Zimmermann, 2001:11). Fuzzy sets were defined by Zadeh (1965) as a class of objects with a degree of continuity. Here, the membership degree of each element in the universe of discourse belongs to a fuzzy set and is represented by a real value between zero and one (Rani et al., 2024). Fuzzy numbers are divided into two as triangular and trapezoidal fuzzy numbers. Triangular fuzzy numbers were used in this study. Zadeh (1965) expressed a triangular fuzzy number mathematically as follows in Equation 1. Definitions of arithmetic solutions with triangular computational numbers can be found in Dubois and Prade (1978), Wagenknecht et al. (2001) and Zadeh (1965).

$$\mu_{\tilde{A}}(X) = \begin{cases} \frac{x-l}{m-l} & l \leq x \leqslant m \\ \frac{u-x}{u-m} & m \leq x \leqslant u \\ 0 & Other \end{cases} \tag{1}$$

The entropy method was proposed by Shannon (1948). This method takes into account the fact that the value of each alternative according to each criterion may vary within a range and may have different behaviors when ranked data is used (Lotfi and Fallahnejad, 2010).

3.1. Fuzzy Entropy

The solution steps of Shannon's fuzzy Entropy based on α-level clusters are as follows (Cavallaro et al., 2016; Lotfi and Fallahnejad, 2010).

Step1. The decision matrix (Equation 1) is formed. Then fuzzy data is converted to interval data using α cut sets using Equations 3 and 4.

$$\tilde{D} = \begin{vmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \cdots & \tilde{x}_{mn} \end{vmatrix} \quad (2)$$

$$(\tilde{x}_{ij})^L_\alpha = l + l * (m - l),\ (\tilde{x}_{ij})^R_\alpha = u + l * (m - u) \quad (3)$$

$$[(\tilde{x}_{ij})^L_\alpha\ ,\ (\tilde{x}_{ij})^R_\alpha] = [\min_{x_{ij}}\{x_{ij} \in R | \mu_{\tilde{x}_{ij}}(x_{ij}) \geq \alpha\}, \max_{x_{ij}}\left\{x_{ij} \in R | \mu_{\tilde{x}_{ij}}(x_{ij}) \geq \alpha\right\}] \quad 0 \leq \alpha \leq 1 \quad (4)$$

Fuzzy data at different confidence levels are transformed into different α-level clusters via Equation 5.

$$B = \begin{vmatrix} [x^L_{11}, x^R_{11}] & [x^L_{12}, x^R_{12}] & \cdots & \cdots & [x^L_{1n}, x^R_{1n}] \\ [x^L_{21}, x^R_{21}] & [x^L_{22}, x^R_{22}] & \cdots & \cdots & [x^L_{2n}, x^R_{2n}] \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ [x^L_{m1}, x^R_{m1}] & [x^L_{m2}, x^R_{m2}] & \cdots & \cdots & [x^L_{mn}, x^R_{mn}] \end{vmatrix} \quad (5)$$

Step 2. The Normalized matrix is formed: The normalized matrix lover bond p^L_{ij} is calculated by Equation 6 and upper bond p^R_{ij} is calculated by Equation 7.

$$p^L_{ij} = \frac{x^L_{ij}}{\sum_{j=1}^{m} x^R_{ij}} \quad j = 1,2,\ldots., m \quad i = 1,2,\ldots, n \quad (6)$$

$$p^R_{ij} = \frac{x^R_{ij}}{\sum_{j=1}^{m} x^R_{ij}} \quad j = 1,2,\ldots., m \quad i = 1,2,\ldots, n \quad (7)$$

Step 3. The lower e^L_i and upper bound e^R_i ranges are determined by entropy using Equations 8 and 9.

$$e^L_i = min\{-e_0 \sum_{j=1}^{m} p^L_{ij} lnp^L_{ij}, -e_0 \sum_{j=1}^{m} p^R_{ij} lnp^R_{ij}\} \ i = 1,2,\ldots, n \quad (8)$$

$$e^R_i = max\{-e_0 \sum_{j=1}^{m} p^L_{ij} lnp^L_{ij}, -e_0 \sum_{j=1}^{m} p^R_{ij} lnp^R_{ij}\} \ i = 1,2,\ldots, n \quad (9)$$

Step 4. The lower d^L_i and upper d^R_i limit range change values are determined by Equations 10 and 11.

$$d^L_i = 1 - e^R_i \quad i = 1,2,\ldots, n \quad (10)$$

$$d^R_i = 1 - e^L_i \quad i = 1,2,\ldots, n \quad (11)$$

Step 5. The lower w^L_i and upper w^R_i values of the criterion weights are determiden by Equations 12 and 13.

$$w^L_i = \frac{d^L_i}{\sum_{s=1}^{n} d^L_s} \quad i = 1,2,\ldots, n \quad (12)$$

$$w^R_i = \frac{d^R_i}{\sum_{s=1}^{n} d^R_s} \quad i = 1,2,\ldots, n \quad (13)$$

Step 6. Determining the average criterion weight by taking the arithmetic average of the lower and upper values

3.2. Fuzzy MARCOS Method

Let $A = \{A_1, A_2, \ldots. A_m\}$ be a set of alternatives and let $C = \{C_1, C_2, \ldots. C_n\}$ be a set of criteria. The solution steps of the method are as follows (Stanković et al., 2020, Pamucar et al, 2021).

Step 1. The fuzzy decision matrix (Equation 15) is created using Equation 14.

In a decision problem with m alternatives and n criteria $\tilde{x}_{ij}$ It is the fuzzy performance value obtained as a result of evaluating alternative i according to j criterion. $\tilde{x}_{ij}$ the decision matrix consisting of performance values as a triangular fuzzy number is shown as follows.

$$\tilde{x}_{ij} = [x^l_{ij}, x^m_{ij}, x^u_{ij}] \quad (14)$$

$$\tilde{X} = \widetilde{x_{ij}} = \begin{vmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \dots & \dots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{21} & \dots & \dots & \tilde{x}_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \dots & \dots & \tilde{x}_{mn} \end{vmatrix} \; i = 1,2, \dots \dots m, j1,2, \dots, \tag{15}$$

Step 2. The extended initial fuzzy matrix (Equation 16) is created using Equations 17 and 18.The extension is performed by determining the fuzzy anti-ideal $\tilde{A}(AI)$ and fuzzy ideal $\tilde{A}(ID)$solution.

$$\tilde{X} = \begin{cases} c) \\ \tilde{A}_1 \\ \vdots \\ \vdots \\ \tilde{A}_m \\ \tilde{A}(ID) \end{cases} \begin{vmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \dots & \dots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{21} & \dots & \dots & \tilde{x}_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \dots & \dots & \tilde{x}_{mn} \\ \tilde{x}_{id1} & \tilde{x}_{id2} & \dots & \dots & \tilde{x}_{idn} \end{vmatrix} \; i = 1,2, \dots \dots m, j1,2, \dots, \tag{16}$$

The fuzzy $\tilde{A}(AI)$is the worst alternative while the fuzzy $\tilde{A}(ID)$is an alternative with the best performance. Depending on type of the criteria, $\tilde{A}(AI)$ and $\tilde{A}(ID)$are as follows. B belongs to the benefit group of criteria while C belongs to the cost group of criteria

$$\tilde{A}(AI) = \underset{i}{min} \tilde{x}_{ij} \; if \; j \in B \; and \; \underset{i}{max} \tilde{x}_{ij} \; if \; j \in C \tag{17}$$

$$\tilde{A}(ID) = \underset{i}{max} \tilde{x}_{ij} \; if \; j \in B \; and \; \underset{i}{min} \tilde{x}_{ij} \; if \; j \in C \tag{18}$$

Step 3. The normalized fuzzy matrix $\tilde{N} = [\tilde{n}_{ij}]$ is created using Equations 19 and 20.

$$\tilde{n}_{ij} = (n_{ij}^l, n_{ij}^m, n_{ij}^u) = \left(\frac{x_{id}^l}{x_{ij}^u}, \frac{x_{id}^l}{x_{ij}^m}, , \frac{x_{id}^l}{x_{ij}^l}\right) if \; j \in C \tag{19}$$

$$\tilde{n}_{ij} = (n_{ij}^l, n_{ij}^m, n_{ij}^u) = \left(\frac{x_{id}^l}{x_{ij}^u}, \frac{x_{id}^m}{x_{ij}^u}, , \frac{x_{id}^u}{x_{ij}^u}\right) if \; j \in B \tag{20}$$

Step 4. The weighted fuzzy matrix $\tilde{V} = [\tilde{v}_{ij}]$ is calculated by multiplying matrix $\tilde{N}$ with the fuzzy weight coefficients of the criterion $\tilde{w}_j$ (Equation 21).

$$\tilde{v}_{ij} = (v_{ij}^l, v_{ij}^m, v_{ij}^u) = \tilde{n}_{ij} \otimes \tilde{w}_j = (n_{ij}^l * w_j^l, n_{ij}^m * w_j^m, n_{ij}^u * w_j^u) \tag{21}$$

Step 5. The fuzzy matrix $\tilde{S}_i$ is calculated by using Equation 22. where$\tilde{S}_i = s_i^l, s_i^m, s_i^u$ represents the sum of the elements of the weighted fuzzy matrix V.

$$\tilde{S}_i = \sum_{i=1}^{n} \tilde{v}_{ij} \tag{22}$$

Step 6. The utility degree of alternatives $\tilde{K}_i$ is calculated by using Equations 23 and 24.

$$\tilde{K}_i^- = \frac{\tilde{s}_i}{\tilde{s}_{ai}} = \left(\frac{s_i^l}{s_{ai}^u}, \frac{s_i^m}{s_{ai}^m}, \frac{s_i^u}{s_{ai}^l}\right) \tag{23}$$

$$\tilde{K}_i^+ = \frac{\tilde{s}_i}{\tilde{s}_{id}} = \left(\frac{s_i^l}{s_{id}^u}, \frac{s_i^m}{s_{id}^m}, \frac{s_i^u}{s_{id}^l}\right) \tag{24}$$

Step 7. The fuzzy matrix $\tilde{T}_i$ is calculated by using Equation 25.

$$\tilde{T}_{ij} = \tilde{t}_{ij} = (t_i^l, t_i^m, t_i^u) = \tilde{K}_i^- \otimes \tilde{K}_i^+ = (k_{ij}^{-l} * k_i^{+l}, k_{ij}^{-m} * k_i^{+m}, k_i^{-u} * k_i^{+u}) \tag{25}$$

Then, it is necessary to determine a new fuzzy number $\tilde{D}$. This value is calculated by using Equation 26.

$$\tilde{D} = (d^l, d^m, d^u) = \underset{i}{max} \tilde{t}_{ij} \tag{26}$$

Then, it is necessary to de-fuzzify the number $\tilde{D}$ obtaining the number $dfcrisp$. This value is calculated by using Equation 27.

$$dfcrisp = \frac{l+4m+u}{6} \tag{27}$$

Step 8. The utility functions in relation to the ideal $f(\tilde{K}_i^+)$ and anti-ideal $f(\tilde{K}_i^-)$ solution is determined by using Equation 28 and 29.

$$f(\tilde{K}_i^-) = \frac{\tilde{K}_i^-}{df_{crisp}} = (\frac{\tilde{k}_i^{-l}}{df_{crisp}}, \frac{\tilde{k}_i^{-m}}{df_{crisp}}, \frac{\tilde{k}_i^{-u}}{df_{crisp}}) \quad (28)$$

$$f(\tilde{K}_i^+) = \frac{\tilde{K}_i^+}{df_{crisp}} = (\frac{\tilde{k}_i^{+l}}{df_{crisp}}, \frac{\tilde{k}_i^{+m}}{df_{crisp}}, \frac{\tilde{k}_i^{+u}}{df_{crisp}}) \quad (29)$$

Step 9. The utility function of alternatives fK_i is determined by using Equation 30.

$$fK_i = \frac{K_i^+ + K_i^-}{1 + \frac{1-f(K_i^+)}{K_i^+} + \frac{1-f(K_i^-)}{K_i^-}} \quad (30)$$

Step 10. Ranking the alternatives based on the final values of utility functions. It is desirable that an alternative have the highest possible value of the utility function.

4. RESULTS

4.1. Data Set

There are 8 thousand 333 kilometers of coastline and a total of 180 ports and piers in Türkiye, excluding marinas (Fig 3). In this research, ports with container handling volumes of more than 1% were determined. These ports are Aliağa (A1), Ambarlı (A2), Antalya (A3), Gemlik (A4), İskenderun (A5), İstanbul (A6), İzmir (A7), Kocaeli (A8), Mersin (A9), Samsun. (A10) and Tekirdağ (A11) ports. The evaluation criteria for these ports were determined by considering the literature. These criteria were determined as container handling import (C1), container handling export (C2), cargo handling import (C3), cargo handling export (C4), number of ships calling at the port (C5), Gross handling of ships calling at the port (C6), Port area (C7), Pier length (C8) and Draft (C9) (Table x) were used. These data were obtained from the statistics of the Ministry of Transport and Infrastructure of the Republic of Türkiye (UAB, 2024) and the Turkish Port Operators Association (TLID, 2024). The data set is 11-year time series data between 2013 and 2023. The reason why these data are limited to 11 years is that all statistics are available on these dates.

Figure 3. Ports in Türkiye (CH, 2024)

4.2. Calculation of Criterion Weights with Fuzzy Entropy Method

Using the 11-year data obtained in the research, the data was converted into triangular fuzzy number form. Here, the minimum value is expressed as l, the mean value as m and the maximum value as u (Wang, 2014) (Equation 31). The decision matrix has been created in this way (App 1).

$$\boldsymbol{p_{ij} = (l_{ij}, m_{ij}, u), \; l_{ij} = min_{1 \le e \le t}^{min}\{x_{ij}(e)\}, \; m_{ij} = \frac{1}{n}\sum_{e=1}^{n} x_{ij}(e), \; u_{ij} = max_{1 \le e \le t}^{min}\{x_{ij}(e)\}}$$

$$\boldsymbol{i = 1, 2, 3, \ldots., m, \; j = 1, 2, 3, \ldots. n \; and \;\; e = 1, 2, 3, \ldots. t}$$

(31)

Fuzzy data was converted to interval data using α cut sets. The α cut-off value was calculated with values of 0.1, 0.5, 0.9, and results with a value of 0.5 were used. Using Equations 3 and 4, the matrix in Equation 5 was created. The interval number matrix for criterion 1 is presented in Table 2.

Table 2. Range data for C1

Ports	Lower	Upper
A1	375745.74	643089.99
A2	963124.99	1119453.99
A3	34744.61	78434.11
A4	312431.09	363027.59
A5	152531.43	293578.43
A6	14192.03	37065.78
A7	173179.74	283817.24
A8	537583.12	860338.38
A9	742053.20	896586.83
A10	10870.88	28495.38
A11	65925.68	188793.68
Total		2497584.11

Normalized interval data were calculated using Equations 6 and 7, and the results for C1 are presented in Table 3.

Table 3. Normalized range data for C1

Ports	Lower	Upper
A1	0.15	0.26
A2	0.39	0.45
A3	0.01	0.03
A4	0.13	0.15
A5	0.06	0.12
A6	0.01	0.01
A7	0.07	0.11
A8	0.22	0.34
A9	0.30	0.36
A10	0.00	0.01
A11	0.03	0.08

Lower and upper bound range entropy calculations were made using Equations 8 and 9, and the results for criterion 1 are presented in Table 4.

Table 4. Lower and upper bound range entropy for C1

Lower Bound	*Upper Bound*
0.48	0.56

Lower and upper limit range change values were calculated using Equations 10 and 11 and are presented in Table 5 for C1.

Table 5. Lower and upper limit range change values for C1

Lower Limit	*Upper Limit*
0.44	0.52

Using Equations 12 and 13, the lower and upper values of the criterion weights were calculated and the results for c1 are presented in Table 6.

Table 6. Table of lower and upper values of criterion weights for C1

Lower Value	*Upper Value*
0.1178	0.1141

Then, the average criterion weights were calculated by taking the arithmetic average (Equations 14 and 15) of the lower and upper values and are presented in Table 7.

Table 7. Table of values of criterion weights for C1

l	*m*	*u*
0.1178	0.1159	0.1141

4.3. Determining the Performanse Rankings of Turkish Ports with Fuzzy MARCOS Method

The decision matrix given in App 1 is also used here. In this research, all of the criteria are benefit criteria. Maximum and minimum values are determined using Equations 17 and 18. Maximum and minimum values for Criterion 1 are presented in Table 8.

Table 8. Max and min values for C1

Min	26206.523	26206.523	26206.523
Max	1042574.8258	1042574.8258	1042574.8258
Min	4488.0000	23896.0682	50235.5000
Max	888816.5000	1037433.4773	1201474.5000

The normalized matrix is determined using Equations 19 and 20. The result obtained for C1 is presented in Table 9.

Table 9. Normalize matrix for C1

	l	*m*	*u*
Weights	0.117808276	0.115930569	0.114052862
A (AI)	0.0251	0.0251	0.0251
A1	0.2315	0.4893	0.7444
A2	0.8525	0.9951	1.1524
A3	0.0140	0.0526	0.0978
A4	0.2794	0.3200	0.3764
A5	0.0683	0.2243	0.3389
A6	0.0043	0.0229	0.0482
A7	0.0982	0.2340	0.3104
A8	0.3708	0.6604	0.9900
A9	0.6357	0.7878	0.9322
A10	0.0030	0.0179	0.0368
A11	0.0000	0.1264	0.2357
A (ID)	1.00000	1.00000	1.00000

The weighted normalized matrix is determined using Equation 21 and taking into account the criterion weights. The result obtained for criterion 1 is presented in Table 10.

Table 10. Weighted normalized matrix for C1

	L	*m*	*u*
A (AI)	0.0030	0.0029	0.0029
A1	0.0273	0.0567	0.0849
A2	0.1004	0.1154	0.1314
A3	0.0017	0.0061	0.0112
A4	0.0329	0.0371	0.0429
A5	0.0081	0.0260	0.0387
A6	0.0005	0.0027	0.0055
A7	0.0116	0.0271	0.0354
A8	0.0437	0.0766	0.1129
A9	0.0749	0.0913	0.1063
A10	0.0004	0.0021	0.0042
A11	0.0000	0.0147	0.0269
A (ID)	0.1178	0.1159	0.1141

The fuzzy matrix $\tilde{S}_i$ is determined by using Equation 22 (Table 11).

Table 11. $\tilde{S}_i$ Values

	l	*m*	*u*
A (AI)	0.0903	0.0905	0.0908
A1	0.3060	0.4900	0.7012
A2	0.4101	0.5666	0.7350
A3	0.0462	0.1930	0.3809
A4	0.2398	0.3563	0.4853
A5	0.1661	0.3848	0.6230
A6	0.0522	0.0921	0.1320
A7	0.2627	0.3348	0.3868
A8	0.4425	0.6172	0.7987
A9	0.3620	0.5329	0.7765

A10	0.1003	0.4444	0.3178
A11	0.1646	0.2391	0.3139
A (ID)	1.0000	1.0000	1.0000

The utility degree of alternatives are determined by using Equation 23 and 24 (Table 12).

Table 12. $\widetilde{K}_i$ Values

Ports	*Fuzzy Ki-*			*FuzzyKi+*		
A1	3.370	5.412	7.769	0.3060	0.4900	0.7012
A2	4.517	6.259	8.144	0.4101	0.5666	0.7350
A3	0.509	2.131	4.220	0.0462	0.1930	0.3809
A4	2.641	3.936	5.376	0.2398	0.3563	0.4853
A5	1.829	4.251	6.903	0.1661	0.3848	0.6230
A6	0.575	1.017	1.462	0.0522	0.0921	0.1320
A7	2.893	3.698	4.285	0.2627	0.3348	0.3868
A8	4.873	6.818	8.849	0.4425	0.6172	0.7987
A9	3.987	5.887	8.603	0.3620	0.5329	0.7765
A10	1.105	4.908	3.521	0.1003	0.4444	0.3178

The $\widetilde{T}_i$ is determined by using Equation 25 (Table 13).

Table 13. $\widetilde{T}_i$ Values

Ports	*Ti*		
A1	3.6757	5.9019	8.4698
A2	4.9269	6.8257	8.8787
A3	0.5551	2.3243	4.6009
A4	2.8813	4.2922	5.8616
A5	1.9953	4.6353	7.5256
A6	0.6268	1.1089	1.5942
A7	3.1561	4.0333	4.6720
A8	5.3155	7.4351	9.6475
A9	4.3492	6.4197	9.3794
A10	1.2048	5.3527	3.8387
A11	1.9768	2.8802	3.7915

The new fuzzy number $\widetilde{D}$ is determined by using Equation 26 and 27 (Table 14).

Table 14. $\widetilde{D}$ Values tables

Ports	*Crisp K-*	*Crisp K+*
A1	5.4644	0.4945
A2	6.2828	0.5686
A3	2.2090	0.1998
A4	3.9602	0.3584
A5	4.2890	0.3881
A6	1.0174	0.0921
A7	3.6621	0.3315
A8	6.8322	0.6183
A9	6.0229	0.5450
A10	4.0431	0.3659

The utility functions in relation to the ideal $f(\widetilde{K}_i^+)$ and anti-ideal $f(\widetilde{K}_i^-)$ solutions are determined by using Equation 28 and 29 (Table 15).

Table 15. Utility functions

Ports	*Crisp F(K-)*	*Crisp F(K+)*
A1	0.0664	0.7334
A2	0.0763	0.8433
A3	0.0268	0.2965
A4	0.0481	0.5315
A5	0.0521	0.5757
A6	0.0124	0.1366
A7	0.0445	0.4915
A8	0.0830	0.9170
A9	0.0732	0.8084

A10	0.0491	0.5427
A11	0.0321	0.3547

The utility function of alternatives $f K_i$ is determined by using Equation 30 (Table 16).

Table 16. Utility functions of altenatives

Ports	*(1-f(K-))/f(K-)*	*(1-f(K+))/f(K+)*
A1	14.0669	0.3635
A2	12.1028	0.1859
A3	36.2865	2.3727
A4	19.7883	0.8813
A5	18.1997	0.7371
A6	79.9257	6.3231
A7	21.4775	1.0345
A8	11.0492	0.0905
A9	12.6695	0.2370
A10	19.3612	0.8428
A11	30.1557	1.8197

Finally, the performanse ranking of Turkish ports is obtained as follows (Table 17).

Table 17. The performanse ranking of Turkish ports

f(K)	*Ranking*	*Port Name*
0.3862	4	Aliağa
0.5156	2	Ambarlı
0.0607	10	Antalya
0.1993	7	Gemlik
0.2346	5	İskenderun
0.0127	11	İstanbul
0.1699	8	İzmir
0.6137	1	Kocaeli
0.4723	3	Mersin
0.2079	6	Samsun
0.0874	9	Tekirdağ

4.4. Sensitivity Analysis

For the sensitivity analysis of the results we obtained with the model created for the research, the results of the model in different Multi-Criteria Decision-making methods were investigated. A ranking was obtained with the Fuzzy Moora Ratio Approach, provided that the criterion weights remained the same.

Table 18. Ranking obtained by fuzzy MOORA ratio method

Fuzzy MOORA Ratio	*Ranking*	*Port Name*
0.1682	4	Aliağa
0.1946	2	Ambarlı
0.0617	10	Antalya
0.1169	6	Gemlik
0.1285	5	İskenderun
0.0309	11	İstanbul
0.1033	7	İzmir
0.2139	1	Kocaeli
0.1855	3	Mersin
0.0928	8	Samsun
0.0787	9	Tekirdağ

The performanse rankings of the ports are presented in Figure 4 for two different methods.

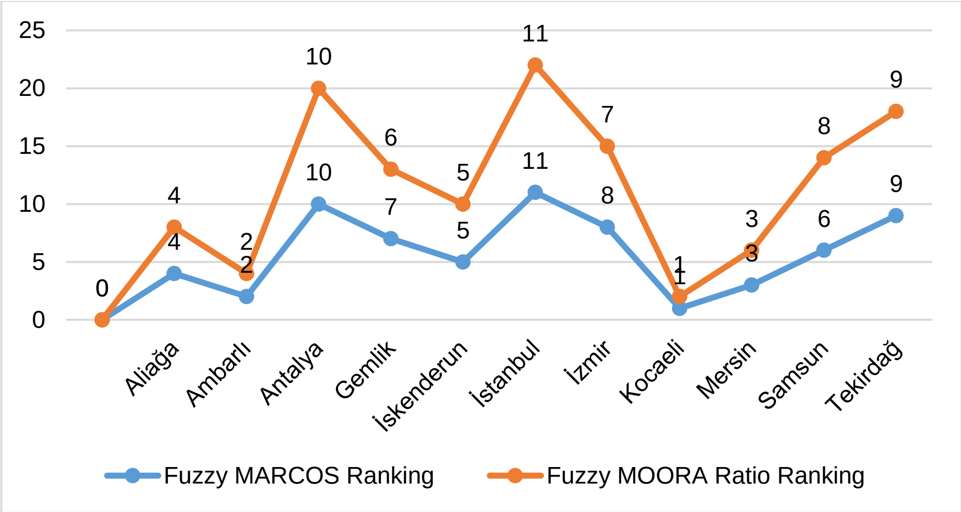

Fig 4. Comparison of port performance obtained using different methods

As can be seen in the figure, Kocaeli port is the most efficient port. Ambarlı is in 2^{nd} rank, Mersin is in 3^{rd} rank, Aliağa is in 4^{th} rank, İskenderun is in 5^{th} rank, Tekirdağ is in 9^{th} ranked and Antalya port is in 10^{th} rank.

5. DISCUSSION and CONCLUSION

Türkiye's ports have many different characteristics as in the world. Capacity differences due to port design and shape should be evaluated differently from the performanse of ports. Ports are the areas of use of the most widely used maritime mode in international transportation. During the pandemic period, it was seen how the disruptions in ports affected the world supply chain and the importance of ports was understood again.

Turkiye is a country where the use of other modes of transportation such as road, rail, air, pipelines is widespread along with maritime transportation. It is a country where the connection between Asia and Europe has been established with the Marmaray line and with the Baku Tbilisi Kars Railway line connections, it is a country that aims to transport from China to Europe by railway lines. Providing port connections of these lines along Türkiye will increase the performanse of ports. After the Ukraine-Russia war, Turkish ports have become important and safe alternatives to prevent disruption in the supply chain flow. In order to utilize these potentials, the performanse of the ports should be evaluated and a discussion environment should be created for development.

For this purpose, in this research, the shares of the ports in the amount of cargo handled in the ports of Turkiye were determined and the performanse of 11 ports with a share of more than 1% was evaluated. As a result of this research, the infrastructure and development process needs of other ports with potential were revealed.

Quantitative panel data were used for the research and different data were transformed into the form of triangular fuzzy numbers. In this way, both the effects of quantitative data and the dynamics of data changes in different years are captured. One of the unique aspects of the study is the use of real quantitative panel data sets and thus taking into account the differences in data size between years. To achieve this, the data were transformed into triangular fuzzy numbers and the weights of the evaluation criteria were determined as triangular fuzzy numbers using the Fuzzy Entropy method. Then, the performanse ranking of the ports was obtained with the Fuzzy MARCOS method. In addition, the sensitivity analysis of this ranking is tested by Fuzzy MOORA Ratio method.

According to the findings, Kocaeli port is the most efficient port in Turkiye according to the nine evaluation criteria, followed by Ambarlı Port (Istanbul), then Mersin port (Mersin). Another factor to be considered in these results is Türkiye's earthquake risk. Kocaeli and Ambarlı ports were affected by the 1999 earthquake and Mersin port was affected by the 2023 earthquake. Therefore, it is necessary to improve the infrastructure security of the ports, which are one of the important factors of Türkiye's foreign trade, against earthquakes. The Black Sea ports, which are at the bottom of the performanse rankings, need to expand their demand base and increase public and private investments. This is very important for the evaluation of the port performance of the Black Sea, which is the shortest route of the Asia-Europe connection.

Managerial deficiencies in ports managed by both public and private subsidiaries can lead to performanse gaps. Improving ports' connectivity to other modes of transportation will have a significant and enhancing effect on increasing demand. The results of this paper can be used by port managers, terminal operators and policy makers to plan the development of the studied ports and improve their performanse levels. Looking at the distribution of cargo handled in our ports and the performanse assessment, it is seen that the highest amount of cargo is handled in the Marmara Region, the Eastern Mediterranean region and the Aegean region. It is important to increase investments in these regions in order not to incur the costs of congestion and inability to respond to demand in the future increases in demand and to eliminate bottlenecks that may occur in undesirable situations such as earthquakes.

There are some limitations for this research. First of all, the research focuses on ports in Turkey, which may limit the applicability of the method for different countries. The dynamics of the evaluation criteria in Turkish ports and the port dynamics of different countries may be different from each other, therefore, this model may provide different outputs, especially regarding the weights of the evaluation criteria. The method proposed in the research can be strengthened by using different methods to strengthen the sensitivity analysis of the model. Each different method causes more restrictions in the ranking. The same rankings obtained in all different methods can only be interpreted. It would not be right to use a clear expression for alternatives with different rankings.

In future studies, Logistics 4.0 compliance and sustainability performances of Turkish ports can also be evaluated. Such studies will make a significant contribution to the development projection of Türkiye's ports.

Conflict of Interest
No potential conflict of interest was declared by the author.

Funding
Any specific grant has not been received from funding agencies in the public, commercial, or not-for-profit sectors.

Compliance with Ethical Standards
It was declared by the author that the tools and methods used in the study do not require the permission of the Ethics Committee.

Ethical Statement
It was declared by the author that scientific and ethical principles have been followed in this study and all the sources used have been properly cited.

REFERENCES

Akgül, E.F. (2018), "Cruise Ports in Türkiye: Analysis of Market Structure and Competitiveness", Turkish *Journal of Maritime and Marine Sciences*, 4(2), 167-179

Akyürek, E. (2017), "Türkiye Karadeniz Limanları Verimlilik Analizi", *Verimlilik Dergisi*, 4, 29-45.

Ali, J. (2022). "A q-Rung Orthopair Fuzzy MARCOS Method Using Novel Score Function and Its Application to Solid Waste Management", *Applied Intelligence,* 52, 8770-8792

Andriotti R.F., Vieira, G.B.B., Sander, N.E.I., Campagnolo, R.R. and Neto, F.J.K. (2021). "Ort Pricing: A Case Study of the Rio de Janeiro Port Authority and Comparison with Others Brazilian Ports", *Case Studies on Transport Policy*, 9, 870-878.

Ateş, A. and Esmer S., (2014)," Farklı Yöntemler İle Türk Konteyner Limanlarının Verimliliği", *Verimlilik Dergisi*1, 61-76

Ateş, A., Esmer S., Çakır E. and Balcı K. (2013), "Karadeniz Konteyner Terminallerinin Göreceli Etkinlik Analizi", *Dokuz Eylül Üniversitesi Denizcilik Fakültesi Dergisi,* 5(1), 1-22.

Balık, İ (2023), "Antalya Limanı'nın Türkiye'de Elleçlenen Yük İçerisindeki Payı ve Yakın Çevresindeki Limanlar ile Karşılaştırmalı Yük Analizi", *Kent Akademisi,* 16(3), 1437-1456. https://doi.org/10.35674/kent.1272994

Baysal, M.E., Uygur, M. and Toklu B. (2004), "A Study of the Relative Efficiency of TCDD Ports, Using Data Envelopment Analysis", *Journal of Faculty of Engineering and Architecture of Gazi University*, 19(4), 437-442

Boztepe, H. (2023), Lojistik Performans Endeksi 2023 (LPI 2023), https://tiud.org.tr/2023/07/17/lojistik-performans-endeksi-2023-lpi-2023/#:~:text=T%C3%BCrkiye%20bir%20%C3%B6nceki%20endeks%20olan,te%2042.%20S%C4%B1rada%20yer%20alm%C4%B1%C5%9Ft%C4%B1r, (Accessed: 01.05.2024).

Büyükozkan, G., Havle C.A. and Feyzioglu, O. (2021), "An Integrated SWOT based fuzzy AHP and Fuzzy MARCOS Methodology for Digital Transformation Strategy Analysis in Airline Industry", *Journal of Air Transport Management*, 97, 102142. https://doi.org/10.1016/j.jairtraman.2021.102142

Cabral, A.M.R. and F. De Sousa Ramos. 2014. "Cluster Analysis of the Competitiveness of Container Ports in Brazil", *Transportation Research Part A: Policy and Practice*, 69, 423–431

Cavallaro, F., Zavadskas, E. and Raslanas, S. (2016), "Evaluation of Combined Heat and Power (CHP) Systems Using Fuzzy Shannon Entropy and Fuzzy TOPSIS", *Sustainability,* 8(6), 1-21. https://doi.org/10.3390/su8060556

Chang, Y.T., and Talley, W.K. (2019). "Port Competitiveness, Efficiency, and Supply Chains: A Literature Review", *Transportation Journal*, 58(1), 1-24. https://doi.org/10.5325/transportationj.58.1.0001

Clark, X., Dollar, D., and Micco, A. (2004), "Port Efficiency, Maritime Transport Costs, and Bilateral Trade", *Journal of Development Economics*, 75, 417-450.

Coğrafyaharita (CH) (2024). http://cografyaharita.com/turkiye_ulasim_haritalari.html, (Accessed: 07.04.2024).

Ding, J.F., Kuo, J.F., Shyu, W.H. and Chou, C.C. (2019). "Evaluating Determinants of Attractiveness and Their CauseEffect Relationships for Container Ports in Taiwan: Users' Perspectives", *Maritime Policy & Management*, 46(4), 466-490. https://doi.org/10.1080/03088839.2018.1562245

Dubois, D., Prade, H. (1978). "Operation on Fuzzy Numbers", *The International Journal of Systems Sciences*, 9(6), 613-626.

Feng, M. (2011). Evaluation of Port Performance: Port Shareholders' Views. In Proceedings of the International Association for Business and Society, 22, 437-448).

Ferrari, C., Percoco, M. and Tedeschi, A. (2010). "Ports and Local Development: Evidence from Italy", *International Journal of Transport Economics*, 37(1), 9-30.

Gamassa, P.K.P. and Chen, Y. (2017). "Comparison of Port Efficiency between Eastern and Western African Ports Using DEA Window Analysis", *2017 International Conference on Service Systems and Service Management, Dalian,* China, 1-6.

Garcia-Alonso, L., Monios, J. and Vallejo-Pinto, J. Á. (2019), "Port Competition Through Hinterland Accessibility: The Case of Spain", *Maritime Economics and Logistics*, 21, 258-277. https://doi.org/10.1057/s41278-017-0085-5

Gonzalez, M.M. and Trujillo, L. (2009), "Efficiency Measurement in the Port Industry: A Survey of the Empirical Evidence", *Journal of Transport Economics and Policy*, 43(2), 157-191.

Kadaifci, C., Umut, A., Seyda, S. and Umut, A. (2019)." A New Rule-Based Integrated Decision Making Approach to Container Transshipment Terminal Selection", *Maritime Policy & Management,* 46 (2), 237-256. https://doi.org/10.1080/03088839.2018.1489149

Li, Z., Xing, Y. and Dong, P. (2024), "A Novel q-Rung Orthopair Fuzzy Best-Worst Method, Shannon Entropy and MARCOS Method for Mobile Medical APP service Quality Evaluation", *Applied Soft Computing Journal*, 155, 111417. https://doi.org/10.1016/j.asoc.2024.111417

Lorencic, V., Twrdy, E. and Lep, M. (2022), "Cruise Port Performance Evaluation in the Context of Port Authority: An MCDA Approach", *Sustainability*, 14, 4181. https://doi.org/10.3390/su14074181

Lotfi, H.F., Fallahnejad, R. (2010). "Imprecise Shannon's Entropy and Multi Attribute Decision Making". *Entropy,* 12, 53–62.

Nemzer L.R. (2017), "Shannon Information Entropy in the Canonical Genetic Code", *Journal of Theoretical Biology*, 26, 158-170. https://doi.org/10.1016/j.jtbi.2016.12.010

Onut, S., Tuzkaya, U.R. and Torun, E. (2011), "Selecting Container Port via A Fuzzy ANP-Based Approach: A Case Study in the Marmara Region, Türkiye", *Transport Policy*,18 (2011) 182-193. https://doi.org/10.1016/j.tranpol.2010.08.001

Özgüven, E.D. and Güngör Ş. (2023), "Blokzinciri Teknolojisi ve Deniz Yolu Taşımacılığı: Türkiye'deki Limanlar Üzerine Bir Değerlendirme", *Dokuz Eylül Üniversitesi Denizcilik Fakültesi Dergisi*, 107,139.

Öztemiz, H.H. and Vatansever, K. (2023), "Türkiye Küresel Konteyner Liman Projeleri: 2035 Yılı Konteyner Trafik Hacmi ve Dış Ticaret Projeksiyonu", *Anadolu Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, 24(3), 261-298.

Pamucar, D., Ecer, F. and Deveci, M. (2021). "Assessment of Alternative Fuel Vehicles for Sustainable Road Transportation of United States Using Integrated Fuzzy FUCOM and Neutrosophic Fuzzy MARCOS Methodology", *Science of The Total Environment*, 788, 147763. https://doi.org/10.1016/j.scitotenv.2021.147763

Poitras, G., Tongzon, J. and Li, H. (1996). "Measuring Port Efficiency: An Application of Data Envelopment Analysis", Working paper, *National University of Singapore*, Singapore.

Rani, P., Chen S-M., Mishra A.R. (2024). "Multi-Attribute Decision-Making Based on Similarity Measure between Picture Fuzzy Sets and the MARCOS Method", *Information Sciences,* 658, 119990. https://doi.org/10.1016/j.ins.2023.119990

Rudjanakanoknas, J. and Suksirivoraboot, W. (2012), "Comparison of Trade Facilitation at Four International Ports in Thailand", *Procedia - Social and Behavioral Sciences*, 48, 215-221. https://doi.org/10.1016/j.sbspro.2012.06.1002

Shannon, C.E. (1948). "A Mathematical Theory of Communication", *The Bell System Technical Journal*, 27(3),379-423

Şişlioğlu, H.M. (2021). "Liman Altyapı Yatırım Kararlarında Kullanılabilecek Analitik Performans Değerlendirme Yöntemi Önerisi", *Uluslararası Stratejik Boyut Dergisi*, 1(2), 143-168.

Stanković, M., Stević, Z., Das, D.K., Subotić, M. and Pamucar, D. (2020), "A New Fuzzy MARCOS Method for Road Traffic Risk Analysis", *Mathematics*, 8(3), 457. https://doi.org/10.3390/math8030457

Stević, Z., Pamucar D., Puška, A., Chatterjee P. (2020), "Sustainable Supplier Selection in Healthcare Industries Using A New MCDM Method: Measurement of Alternatives and Ranking According to Compromise Solution (MARCOS)", *Computers & Industrial Engineering*, 140, 106231. https://doi.org/10.1016/j.cie.2019.106231

TLID (Port Operators Association of Türkiye). (2023). Turkısh Port Sector 2023 Report, Sustainable Ports.https://www.turklim.org/en/sector-statistics/. (Accessed: 09.03.2024).

TLID (Port Operators Association of Türkiye). (2024). https://www.turklim.org/en/sector-statistics/. (Accessed: 15.03.2024).

UAB (Türkiye Ulaştırma ve Altyapı Bakanlığı). (2024). https://denizcilikistatistikleri.uab.gov.tr/, (Accessed: 21.04.2024).

UTİKAD (International Transportation and Logistics Service Providers Association. (2022). "Lojistik Sektör Raporu 2022", https://www.utikad.org.tr/UTIKAD-Raporlari, (Accessed: 15.03.2024).

Wagenknecht, M., Hampel, R. and Schneider, V. (2001). "Computational Aspects off Fuzzy Arithmetics Based on Archimedean t-Norms", *Fuzzy Sets and Systems*,123, 49-62.

Wang, W., Han, X., Ding, W., Wu, Q., Chen, X. and Deveci, M. (2023), "A Fermatean fuzzy Fine-Kinney for occupational risk evaluation using extensible MARCOS with prospect theory", *Engineering Applications of Artificial Intelligence,* 117, 105518. https://doi.org/10.1016/j.engappai.2022.105518

Wang, Y.a Wang, W., Wang Z., Deveci, M., Roy, S.K., Kadry, S. (2024), "Selection of Sustainable Food Suppliers Using the Pythagorean Fuzzy CRITIC-MARCOS Method", *Information Sciences,* 664, 120326. https://doi.org/10.1016/j.ins.2024.120326

Wang, Y-J. (2014). "The Evaluation of Financial Performance for Taiwan Containershipping Companies by Fuzzy TOPSIS", *Applied Soft Computing*, 22, 28-35. https://doi.org/10.1016/j.asoc.2014.03.021

World Bank (WB) (2024), LPI, https://lpi.worldbank.org/international/global, (Accessed: 10.03.2024).

Zadeh, A.L. (1965). “Fuzzy Sets”, *Information and Control,* 8, 338-353.

Zimmermann, H.J. (2001). “Fuzzy Set Theory-and Its Applications”, Fourth Edition, Springer, New York.

APPENDIX

Table A1. Decision matrix

		Ports										
Variables	*Statistics*	*Aliağa*	*Ambarlı*	*Antalya*	*Gemlik*	*İskenderun*	*İstanbul*	*İzmir*	*Kocaeli*	*Mersin*	*Samsun*	*Tekirdağ*
KİHR	Min.	241404.5	888816.5	14616	291254.5	71246.75	4488	102364.5	386632.25	662774.75	3103	50
	Avg.	510086.9773	1037433.477	54873.22727	333607.6818	233816.1136	23896.06818	243994.9773	688534	821331.6591	18638.75	131801.3636
	Max.	776093	1201474.5	101995	392447.5	353340.75	50235.5	323639.5	1032142.75	971842	38352	245786
KİTH	Min.	210999.75	907376.75	22088.5	247418	72974.5	5241.25	141183.25	375291.25	655317.5	5230	42
	Avg.	437198.7955	1093324.045	65596.77273	309664.7273	233223.2727	33340.45455	262525.8636	668924.8864	808131.0682	25578.25	127506.4091
	Max.	700417.25	1286772.5	103017	380790	346880.5	64762.5	325859	994032.75	1013549.5	50190	256706
YİHR	Min.	11135082	8667535	1847631	4533083	5673397	55916	2684372	11957160	11949003	748768	623474
	Avg.	16734143.55	9937796.909	2927571.545	5563505.455	12700619.91	363767.7273	4330735.818	18495659	14605786.91	1927678.273	2989381.364
	Max.	23608450	11232543	4649718	7827529	20958847	881202	5485301	26735825	17768478	3151033	6137945
YİTH	Min.	23998647	9613277	659898	5343145	21293394	339893	3376133	39116118	16985102	6298324	10130815
	Avg.	35631328.73	12118716.27	1271917.273	5837472.727	32912055.09	826668.5455	4183954.091	41942448.82	19016018.18	7631766.364	12747426.82
	Max.	45630695	14999109	2092535	6382023	39047212	1329293	5117537	46622671	23003837	8911006	16684661
GS	Min.	4814	3453	524	3308	3591	538	1530	8714	3874	2349	1860
	Avg.	5334.90909	4303.54545	931.181818	3711.27273	4177	2107.09091	1958.63636	9792.36364	4253.72727	2728.72727	2486.81818
	Max.	6329	5574	2136	4069	4791	3683	2495	10621	5076	3088	2918
GGR	Min.	51828145.3	77363574.7	6233438	46500415.2	4791	2389	2047	113266618	61023512.7	11217814.9	15439791.5
	Avg.	87928781	88927828.3	11522190.9	58121370.4	55762501.8	21638168.8	28253522.3	141413526	72345678.3	14786211.2	42025945.1
	Max.	121843279	102732900	37337391.1	63544248.3	80686076.8	40054091	48245747	170788848	85526882.7	17932941	63515954
LU	Min.	164	930	342	1200	265	980	3650	36	100	408	2310
	Avg.	652.25	3465	342	1625	1015	980	3650	476.318182	1068.25	1038	2310
	Max.	1689	6000	342	2050	2300	980	3650	1455	3370	1756	2310
LA	Min.	148930	50205	23097	211000	40000	29000	635000	3060	60000	210000	152514
	Avg.	316965	69978	1030509	730500	376132	29000	635000	179558	656678	614667	152514
	Max.	485000	89750	2037920	1250000	1000000	29000	635000	60000	1253355	1189000	152514
D	Min.	21.5	13	9.5	14.5	7.5	13	6	8.5	9.8	11	12
	Avg.	24.75	15	9.5	25.25	15.287	13.5	8	16.8055556	12.8666667	379.666667	12
	Max.	28	17	9.5	36	27	14	10	30	15.8	20	12

T.C. SANAYİ VE
TEKNOLOJİ BAKANLIĞI

#MİLLİ TEKNOLOJİ HAMLESİ

STRATEJİK ARAŞTIRMALAR VE VERİMLİLİK GENEL MÜDÜRLÜĞÜ