Erciyes Üniversitesi
İktisadi ve İdari Bilimler Fakültesi Dergisi
e-ISSN: 2630-6409

Araştırma Makalesi | Research Article
Yayın Tarihi: 30 Nisan 2026 | Published: April 30, 2026
doi: 10.18070/erciyesiibd.1788717

***Sorumlu Yazar/ Corresponding Author:**
Nazife ŞAHİN MACİT,
nazfe.sahin@gmail.com

JEL:
C38, Q56, R41

Geliş: *22 Eylül 2025*
Received: *September 22, 2025*
Kabul: *22 Aralık 2025*
Accepted: *December 22, 2025*
Yayın: *30 Nisan 2026*
Published: *April 30, 2026*

Atıf / Cited as (APA):
Şahin Macit, N., (2026), From Logistics to Productivity Sustainable Development: An Integrative Analysis of LPI and SDGs Indices for G20 Countries , Erciyes Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 73, 59-71, doi: 10.18070/erciyesiibd.1788717

FROM LOGISTICS TO PRODUCTIVITY SUSTAINABLE DEVELOPMENT: AN INTEGRATIVE ANALYSIS OF LPI AND SDGS INDICES FOR G20 COUNTRIES

NAZİFE ŞAHİN MACİT[1*]

[1] Dr. Öğr. Üyesi , Gümüşhane Üniversitesi Kelkit Aydın Doğan Meslek Yüksekokulu Elektrik ve Enerji Bölümü, nazfe.sahin@gmail.com

ABSTRACT

This study examines the interaction between logistics performance and sustainable development in G20 countries from a holistic perspective, based on the 2022 Logistics Performance Index (LPI) and selected Sustainable Development Goals (SDGs) indicators. Correlation analysis aims to reveal the extent and direction of the relationship between the LPI overall score and its sub-dimensions, as well as the SDGs indicators. This is followed by a comprehensive ranking of countries' performance using multi-criteria decision-making (MCDM) and Borda methods. Correlation analyses demonstrate significant positive relationships, particularly between customs clearance efficiency, logistics service quality, and on-time delivery sub-dimensions, as well as import disproportionality; between customs clearance efficiency and access to basic drinking water services; and between SDGs indicators, such as on-time delivery and access to basic sanitation services. Conversely, a negative but insignificant relationship was found between the malnutrition rate and the LPI and its sub-indicators, and no significant correlation was found between access to electricity and the LPI indicators. The FANMA, SWEI, and TODIFFA methods were used to assess country performance, taking into account the criteria weights calculated using the SITDE method, and the resulting data were then combined using the Borda method. The integrated assessment revealed that Germany, France, and China had the highest integrated logistics and sustainable development performance, while South Africa, Indonesia, and Mexico had the lowest performance. The results demonstrate that advanced logistics infrastructure supports both economic competitiveness and contributes to sustainable development, offering important insights for policymakers regarding the integration of logistics and sustainability strategies.

Keywords: borda method, correlation analysis, logistics performance index, multi-criteria decision making, sustainable development goals

LOJİSTİK VERİMLİLİKTEN SÜRDÜRÜLEBİLİR KALKINMAYA: G20 ÜLKELERİ İÇİN LPI VE SDGS ENDEKSLERİNİN ENTEGRATİF ANALİZİ

ÖZ

Bu çalışma, G20 ülkelerinde lojistik performans ile sürdürülebilir kalkınma arasındaki etkileşimi, 2022 yılı Lojistik Performans Endeksi (LPI) ve seçilmiş Sürdürülebilir Kalkınma Hedefleri (SKH) göstergeleri temelinde, bütüncül bir perspektifle incelemiştir. Korelasyon analizi ile LPI genel skoru ve alt boyutları ile SKH göstergeleri arasındaki ilişkinin boyutunu ve yönünü; sonrasında çok kriterli karar verme (ÇKKV) ve Borda yöntemleri ile ülkelerin bütünleşik performans sıralamasını açığa çıkarmayı hedeflemektedir. Korelasyon analizleri, özellikle gümrük işlemleri verimliliği, lojistik hizmetlerin kalitesi ve zamanında teslimat alt boyutları ile ithal oransızlaşma arasında; gümrük işlemleri verimliliği ile temel içme suyu hizmetlerine erişim arasında, zamanında teslimat ile temel sanitasyon hizmetlerine erişim gibi SKH göstergeleri arasında anlamlı pozitif ilişkiler olduğunu göstermiştir. Diğer taraftan, yetersiz beslenme oranı ile LPI ve alt göstergeleri arasında negatif fakat anlamsız bir ilişkinin olduğu, ayrıca elektriğe erişim ile LPI göstergeleri arasında da anlamlı bir korelasyon bulunmadığı tespit edilmiştir. SITDE yöntemi ile hesaplanan kriter ağırlıkları hesaba katılarak ülkelerin performanslarının değerlendirilmesinde FANMA, SWEI ve TODIFFA yönteminden faydalanılmış ve ortaya çıkan sonuçların birleşimi ise Borda yöntemi ile gerçekleştirilmiştir. Yapılan bütünleşik değerlendirme sonucunda Almanya, Fransa ve Çin'in en yüksek entegre lojistik ve sürdürülebilir kalkınma performansına sahip olduğu; Güney Afrika, Endonezya ve Meksika'nın ise en düşük performans sergilediği ortaya çıkmıştır. Sonuçlar, gelişmiş lojistik altyapının hem ekonomik rekabet gücünü hem de sürdürülebilir kalkınmaya katkıyı desteklediğini ortaya koymakta ve politika yapıcılar için lojistik ve sürdürülebilirlik stratejilerinin entegrasyonuna yönelik önemli ipuçları sunmaktadır.

Anahtar Kelimeler: borda metodu, çok kriterli karar verme, korelasyon analizi, lojistik performans indeksi, sürdürülebilir kalkınma hedefleri

[An extended English abstract is available at the end of the article.]

1. Introduction

The quality of logistics systems stands out as a key factor directly shaping countries' international trade performance and competitiveness. This quality is largely shaped by government investments in advanced infrastructure, planned policies, and services provided. Macro-level parameters include separating transportation infrastructure, optimizing customs procedures, and establishing standard regulations to expand government logistics activities. This process directly contributes to countries' economic growth and international competitiveness. Therefore, a strong relationship exists between logistics performance and economic competitiveness (Kabak et al., 2020, p. 238).

Logistics performance is considered a leading indicator of a country's overall productivity and plays a critical role in assessing the effectiveness of supply chains. Logistics encompasses the planning, coordination, and management of the flow of materials, products, and resources, from raw material procurement to the delivery of the final product to the consumer. Effective logistics activities directly shape economic development by ensuring the safe and efficient transportation of products at the right time (Cheng, 2024, p. 1).

Logistics performance on a global scale is closely linked to the sustainability and efficiency of international trade. Logistics encompasses a range of multidimensional processes, including freight transportation, warehousing, customs procedures, brokerage, and payment systems. High logistics performance not only supports economic growth but also has a significant impact on poverty reduction and achieving the Sustainable Development Goals (Mariano et al., 2017, p. 166). In this context, the Logistics Performance Index (LPI), developed by the World Bank, stands out as an international indicator measuring countries' logistics capacity. The LPI consists of six key components: customs procedures, transportation infrastructure, regularity of international shipments, quality of logistics services, shipment traceability, and on-time delivery (Liu et al., 2018, p. 283; Mešić et al., 2022, p. 13). The LPI is an interactive tool that helps countries identify the challenges and opportunities they face in trade logistics, improve their performance, and develop strategic plans. Effective logistics services not only increase product mobility, security, and speed but also contribute to reducing costs in cross-border trade. Under conditions of globalization and increasing competition, logistics efficiency contributes to increased trade volume by reducing costs and ensuring product safety (Stević et al., 2024, pp. 1-2; Suki et al., 2021, pp. 595-596).

However, the high levels of fossil fuel consumption and CO_2 emissions generated by logistics activities have negative impacts on environmental sustainability. This situation highlights the dual role of logistics, which provides economic and social benefits while also posing environmental risks (Shamout, 2024, pp. 6629-6630). In this context, the Sustainable Development Goals (SDGs) provide a global framework that aims to balance economic development, social welfare, and environmental protection (Asadikia et al., 2023, p. 255). In recent years, the importance of the relationship between logistics and sustainability has increased. While logistics activities provide socio-economic benefits such as infrastructure development, accessibility, employment creation, and poverty reduction, they have also begun to put pressure on the ecosystem due to fossil fuel use and environmental externalities. This necessitates the development of a sustainable logistics approach and the adoption of policies that balance economic, social, and environmental dimensions (Loucanova et al., 2024, p. 317).

Logistics performance (LP) plays a critical role in achieving the United Nations' SDGs. Effective logistics systems have a direct impact on economic growth, industrial sustainability, access to healthcare, and resource efficiency by ensuring the rapid and efficient movement of goods, resources, and services. Strong logistics networks facilitate trade, reduce costs, create jobs, and contribute to sustainable industrialization by supporting resilient infrastructure and industrial innovation. In the healthcare sector, logistics has played a critical role in the distribution of vaccines and medical supplies, contributing to the reduction of inequalities in access to healthcare. Furthermore, through optimizing resource use, reducing waste, disseminating green technologies, and implementing a circular economy, logistics supports responsible production and consumption processes. Furthermore, the strategic importance of the logistics sector in deploying renewable energy technologies and accelerating the transition to clean energy is increasingly evident. Therefore, logistics performance not only provides economic benefits, but it also directly shapes the achievement of sustainable development goals in the areas of health, environment, energy, and social welfare (Agrawal et al., 2022, pp. 3669-3670; Rehman & Hasan, 2025, pp. 2-5).

In this context, one of the areas where the interaction between logistics performance and sustainable development can be most concretely observed is among the G20 countries. Representing approximately 85% of the world economy and 75% of trade, these countries directly impact not only their own economic growth but also the stability of global value chains through their logistics activities due to their weight in global production and trade (Gelmez et al., 2024, p. 340; Özarı, 2025, p. 1294). With their high production capacities and large trade volumes, G20 countries play a leading role in improving logistics performance; they also bear significant responsibilities in terms of sustainability in areas such as resource consumption, carbon emissions, and waste management (Campoli et al., 2025, p. 4; Pehlivan et al., 2024, p. 6). Therefore, an integrated evaluation of the Logistics Performance Index (LPI) and Sustainable Development Indicators (SDGs) data is of critical importance in revealing both the competitiveness of G20 countries in global trade and their contribution to sustainable development.

Accordingly, this study examines the relationship between logistics performance (LPI) and sustainable development indicators (SDGs) in G20 countries using an integrated approach. Due to data limitations, the Russian Federation, Saudi Arabia, and Argentina have been excluded from the analysis, and the study is limited to the remaining 16 members of the G20. The research aims to answer the following questions:

• Is there a relationship between the Logistics Performance Index (LPI) and related sub-indicators and selected SDGs sub-indicators within the context of G20 countries? If so, to what extent and direction?

• How does an integrated assessment conducted using logistics and sustainability indicators in G20 countries using the MCDM and Borda methods reveal the performance rankings of countries?

For the analysis, LPI and SDGs data were selected for 2022, but due to the lack of SDGs data for the Russian Federation, Saudi Arabia, and Argentina, these countries were excluded. Therefore, the integrative analysis was conducted on 16 G20 countries. Two main methods were used in the study: Bivariate correlation analysis revealed the linear relationships between the LPI and SDGs indicators, while the multi-criteria decision-making (MCDM) method allowed for the assessment of integrated sustainability performance on a country basis by considering the weighting and priority relationships between indicators. The Skewness Impact Through Distributional Evaluation (SITDE) method was used for weighting the indicators because it takes into account skewness and outliers to obtain more objective and robust results (Gopisetty & Sama, 2025). The FANMA (a novel hybrid technique named after its developers), Sum Weighted Exponential Information (SWEI), and the Total Differential of Alternative (TODIFFA) methods were used to assess and rank countries' sustainability levels based on integrated indicators. The FANMA method (Mandal et al., 2025) was chosen because it provides a reliable and consistent ranking among alternatives based on the distance-to-ideal-point principle. The SWEI method (Dwivedi & Sarma, 2025a) was chosen because it incorporates entropy-based weighting and exponential information measures that increase decision accuracy. The TODIFFA method (Gligorić et al., 2024) was chosen because it evaluates cost and benefit variables together and clearly reveals relative differences. Finally, the Borda counting method was used to combine the rankings obtained by different methods. Thus, the results from the methods were integrated to produce the final country ranking. This combination of LPI and SDGs data allows for a comprehensive performance assessment that encompasses not only countries' logistics efficiency or individual SDGs indicators, but also their competitiveness in global trade and their contribution to sustainable development.

The remaining sections of the study are structured as follows. The second section provides a detailed overview of studies conducted on the Logistics Performance Index (LPI) and Sustainable Development Indicators (SDGs), as well as research examining the LPI and SDGs together, and literature on evaluating country performance within the context of the LPI and SDGs through multi-criteria decision-making (MCDM) methods. The third section presents the dataset and methods. The fourth section addresses the findings resulting from the application of the methods. The final section discusses the results and offers recommendations.

2. Literature review

The literature review of previous studies focused on logistics performance (LPI), sustainable development goals (SDGs), and studies that address these two areas together. Furthermore, studies evaluating country performance using Multi-Criteria Decision Making (MCDM) methods, considering SDGs and LPI indicators, were reviewed. Furthermore, existing studies on the SITDE, SWEI, FANMA, and TODIFFA methods discussed within the scope of the research were reviewed. The findings of these studies are summarized under subheadings. Studies on country performance evaluations conducted specifically using MCDM methods and LPI and SDGs indicators are presented in Table 1, while the relevant literature review on the methods (SITDE, SWEI, FANMA, and TODIFFA) is presented in Table 2.

As shown in Table 1, the studies demonstrate the comprehensive application of various MCDM methods to evaluate countries' logistics performance, sustainability levels and progress towards the SDGs. Indices of environmental logistics have been developed in the literature (Lu et al., 2019). Performance based on the LPI has been examined using the CRITIC-MARCOS approach (Mešić et al., 2022), the SD-COPRAS-SAW approach (Gelmez et al., 2024), and entropy-based hybrid approaches (Stević et al., 2024). The PSI and PIV methods have been used to compare logistics competitiveness (Biswas & Anand, 2020). Additionally, the following methods are included among the sustainability and SDGs indicators: SWI (Dwivedi & Sharma, 2025b); MPSI-RAPS (Ersoy et al., 2026); CODAS, EDAS, TOPSIS, VIKOR and WASPAS (Brodny & Tutak, 2023a); CoCoSo-Shannon Entropy (Stanujkic et al., 2020); FF-SWARA (Ayyildiz, 2022); Fuzzy SMART and ARAS (Candan & Toklu, 2024); and AHP (Martín & Carnero, 2019).

2.1. Literature on the relationship between Logistics Performance Index (LPI) and sustainability

Khan et al. (2025) used the dynamic Autoregressive Distributed Lag (ARDL) method to examine the impact of economically, environmentally, and socially sustainable logistics in Saudi Arabia between 1990 and 2022, and compared the pre- and post-Vision 2030 period. The evaluations revealed that Vision 2030 plays a critical role in promoting sustainable activities, economic diversification, and increasing social welfare, as well as its impact on performance indicators in industrial and manufacturing sectors. Aboul-Dahab and Ibrahim (2020) examined the logistics performance of Arab countries according to the 2018 LPI report and the relationship between these countries' economic performance and logistics performance. Using linear regression, correlation, and K-means cluster analysis, the study found a generally weak to moderate relationship between nominal GDP and logistics performance (LPI), while sub-indicators and political and infrastructural factors played a critical role in determining LPI scores. Larson (2021) tested the relationships between national logistics performance and sustainability dimensions within the scope of the Sustainable Society Index (SSI) and the World Bank Logistics Performance Index (LPI) using regression analysis. The results revealed that logistics performance is positively affected by social sustainability.

Suki et al. (2021) examined the effects of logistics performance on economic growth and carbon emissions in leading Asian countries using advanced panel data analysis based on IPAT and STIRPAT models and determined that logistics performance supports economic development while reducing environmental impacts. Shamout (2024) examined the impact of logistics performance on environmental performance in 47 countries in Europe and Central Asia during the period 2007–2018 using the Poisson Pseudo Maximum Likelihood (PPMLHDFE) method, controlling for macroeconomic variables. The results indicated that logistics performance has a positive contribution to environmental health and ecosystem vitality, while economic growth and industrialization have a negative impact on environmental quality. Rashidi and Cullinane (2019) calculated sustainable operational logistics performance (SOLP) efficiency scores for each country by applying Data Envelopment Analysis (DEA) to evaluate sustainable logistics performance in OECD countries and compared their results with the Logistics Performance Index (LPI). The results show that the SOLP better reveals countries' productivity sources than the LPI and provides complementary and more useful information for policy development. Kabak et al. (2020) examined the bidirectional relationship between countries' competitiveness levels and logistics performance using methods such as Bayesian Network, Partial Least Squares (PLS) and Importance-Performance Map Analysis (IPMA) using LPI and GCI data for the years 2010-2012-2014-2016. The results reveal that competitiveness elements such as infrastructure, business maturity, financial market development, and higher education play a critical role in increasing logistics performance, and that logistics performance, in particular, has a positive effect on market size. Starostka-Patyk et al. (2024) developed a new index called the Green Logistics Performance Index (GLPI) by combining the logistics performance index (LPI) and environmental performance index (EPI) data for the European Union countries and evaluated the green logistics performance of the countries by comparing the data for the years 2010 and 2018.

Sheikh et al. (2023) developed a comprehensive model comprising 19 indicators under four main factors, utilizing exploratory factor analysis (EFA) to measure maritime logistics performance, thereby overcoming the inadequacies of existing indices. Cheng et al. (2024) used panel data covering 43 countries for the period 2010-2016 to demonstrate the positive effect of logistics performance (LPI) on the ecological footprint (EFP) by controlling for economic indicators (import, export, GDP, adjusted national income) using a pooled regression model. They emphasized that logistics performance plays a critical role in sustainable and environmentally friendly supply chains. Mariano et al. (2017), in their study covering 104 countries, evaluated logistics performance through CO2 emissions using the SBM-DEA method and developed the Low-Carbon Logistics Performance Index (LCLPI). Changes over time were analyzed using the Malmquist index and window analysis, with the highest performance observed in Japan, Germany, Togo, Benin, and the United States. The BRICS countries, particularly China, were also examined in detail. Zaman and Shamsuddin (2017) examined the impact of logistics performance indices on national-scale economic indicators such as energy use, environmental degradation, and economic health using panel data from 2007 to 2014 for 27 European countries. The findings reveal that different dimensions of logistics performance have various environmental and economic impacts, including increasing renewable energy use, reducing carbon emissions, and promoting economic growth, which offer important implications for regional green supply chain management.

Jonasíková et al. (2025) examined the Logistics Performance Index (LPI) in selected countries between 2007 and 2022, using time series and cluster analysis. The results revealed that Western European countries have stable and high logistics performance, while Eastern European countries lag behind due to infrastructure deficiencies and regulatory barriers. Varma and Shah (2021) examined the relationship between the Logistics Performance Index (LPI) and the Human Development Index (HDI) using 2018 data from 154 countries. A significant and positive relationship was found between the two variables in linear regression analysis conducted with SPSS. Harsono and Wahyuningsih (2023) analyzed the effects of the Logistics Performance Index (LPI) and other factors on sustainability performance in G20 countries, focusing on Indonesia, using panel data analysis. They found that logistics has positive effects on environmental and economic sustainability, but no significant effect on social sustainability.

Hamidova et al. (2024), in their study with data from 60 countries that are members of the International Transport Forum (ITF), demonstrated that CO_2 emissions from transportation affect countries' logistics efficiency (LPI) and transportation infrastructure investments and transportation volume through Granger causality and panel regression analyses. Wan et al. (2022), in their study with a panel data set covering 22 developing countries for the period 2007–2018, revealed the negative effects of logistics performance on environmental sustainability, while using the Moment Quantile Regression (MM-QR) method, they revealed that green innovation, renewable energy use, and economic globalization play important roles in reducing CO_2 emissions. Dimitrievska et al. (2020), in their study with Logistics Performance Indicator (LPI) data from 160 countries for the period 2007–2018, used the artificial neural network method to evaluate logistics performance and identify areas for improvement. The study also utilized Pearson correlation analysis to examine the relationships among the six key variables that comprise the LPI (customs, infrastructure, ease of international transportation, logistics service quality, track and trace, and on-time delivery). The analysis revealed that all these variables have a significant and strong positive relationship with the LPI. Jayalakshmi and Praveen (2024) examined the relationship between Gross Domestic Product (GDP), foreign trade balance (GSR), and the Logistics Performance Index (LPI) using multiple regression and correlation analyses. Consequently, significant correlations existed between the LPI and both GDP and GSR, and both variables together explained 45% of the variance in the LPI.

2.2. Literature review on Sustainable Development Goals (SDGs)

Akhtar et al. (2025) examined the impact of the ecological footprint (EA) on blue economy sustainability using panel datasets for the period 2000–2021 in G20 countries using Bayesian neural network (BNN), OLS, fixed effects, and two-step generalized moments methods. The study revealed that the ecological footprint has a negative impact on the blue economy, while greenhouse gas emissions, population growth, and economic growth have positive effects. Li et al. (2025) examined the impact of landscape structures and ecosystem services on the Sustainable Development Goals (in the categories of basic needs, governance, and targets) in the Dangala and Bukhara regions of Central Asia. The study identified priority action areas for regional sustainable development using landscape indices, ecosystem service assessment models, regression analyses, factor analysis, and structural equation modeling. Medina-Hernández et al. (2023), using the HJ-Biplot multivariate analysis method to examine the 2021 Sustainable Development Indicators for 125 countries, found that countries in the global North have strong sustainability characteristics in terms of economic growth and access to basic services, but need development in environmental protection and responsible production and consumption, while countries in the global South need to develop more policies, particularly in areas such as poverty, health, education, and infrastructure. Using a panel data model, Liu et al. (2023) found that the landscape patterns and ecosystem services of nature reserves in the Qinghai-Tibet Plateau positively contribute to achieving the Sustainable Development Goals, while carbon sequestration has positive effects and habitat quality has negative effects on certain indicators. Gong et al. (2024) examined the relationships between mangrove restoration and the Sustainable Development Goals (SDGs) using network analysis, demonstrating that mangrove loss demonstrates strong complementarity with SDG 12 (responsible production and consumption) and SDG 13 (climate action), particularly in the Indonesian context. Asadikia et al. (2023) developed a holistic prioritization method using benchmarking, bivariate, and network analysis to identify indicators to be used in assessing SDGs performance in Australia. The analysis revealed that one-third of the indicators required high priority and had complex interactions. Thanyawatpornkul (2024) demonstrated through a systematic literature review that artificial intelligence makes significant contributions to solving global problems, such as climate change, health, access to clean water, and renewable energy, in line with the Sustainable Development Goals (SDGs). However, the review also highlights the potential of these technologies to exacerbate economic inequalities. Raman et al. (2024) systematically analyzed both direct and transferable connections between SDG 12 and other sustainable development goals, emphasizing that SDG 12 and SDG 7, 11, 13, and 15 are interrelated and that they inform policy recommendations, such as e-waste management, carbon emissions reduction, life improvement support, and the development of green products.

TABLE 1 | Previous studies conducted using MCDM Methods, taking into account SDGs and LPI indicators

Author(s) (Year)	Indicator	Method	Country	Problem/Objective
Lu et al. (2019)	Environmental Logistics Performance Index (ELPI)	RAM-DEA	112 Countries	To develop an environmental logistics performance index (ELPI) to evaluate the overall performance of green transportation and logistics practices
Mešić et al. (2022)	Logistics Performance Index (LPI)	CRITIC-MARCOS	Western Balkan countries (Bosnia and Herzegovina, North Macedonia, Albania, Serbia, Montenegro)	Evaluation of countries' logistics performance
Gelmez et al. (2024)	Logistics Performance Index (LPI)	SD-COPRAS-SAW	G20 Countries	Evaluation of countries' logistics performance
Stević et al. (2024)	Logistics Performance Index (LPI)	ENTROPY, MCRAT, SAW, TOPSIS, FUCA	118 Countries	Evaluation of countries' logistics performance
Biswas and Anand (2020)	LPI, ICT, CO_2 intensity	PSI and PIV	G7 and BRICS countries	Comparative assessment of countries in terms of logistics competitiveness
Dwivedi and Sharma (2025b)	Economic, social, and environmental SDGs indicators	SWI (Sum-Weighted Information)	Indian states	Evaluation of countries' sustainability performance
Ersoy et al. (2026)	SDGs indicators	MPSI-RAPS	27 EU countries	Evaluation of countries' SDGs performance
Brodny and Tutak (2023b)	SDG 9	Entropy, CRITIC, standard deviation, TOPSIS, WASPAS, EDAS, Spearman and Kendall's Tau	27 EU countries	Assessment of countries' progress toward SDG 9 ("Industry, Innovation and Infrastructure")
Brodny and Tutak (2023a)	SDG 7 and SDG 13	CODAS, EDAS, TOPSIS, VIKOR, WASPAS	27 EU countries	Evaluation of countries' energy and climate sustainability
Stanujkic et al. (2020)	SDGs indicators	CoCoSo and Shannon Entropy	EU countries	Assessment of countries' SDGs performance
Ayyildiz (2022)	SDG-7 indicators	FF-SWARA	Turkey	Determining the importance ranking of indicators for SDG-7 (Affordable and Clean Energy)
Candan and Toklu (2024)	SDGs security indicators	Fuzzy SMART, ARAS	EU countries	Evaluation of countries' security performance in the context of sustainable development
Brodny and Tutak (2023c)	SDG 9-related indicators	CODAS, CoCoSo, Shannon Entropy, CRITIC, Kendall Ranking, Spearman Ranking	Poland	Assessment of SDG 9 implementation ("Build resilient infrastructure, promote sustainable industrialization and foster innovation")
Martín and Carnero (2019)	SDGs indicators	AHP	EU countries	Evaluation of countries' sustainable development across multiple dimensions

TABLE 2 | Previous applications of MCDM methods (SITDE, SWEI, FANMA, TODIFFA) in related research areas

Author(s) (Year)	Method	Problem/Objective
Gopisetty and Sama (2025)	SITDE, CRITIC, ENTROPY, MEREC, SD	Selection of electric vehicles
Mandal et al. (2025)	FANMA, WASPAS	Evaluation of renewable energy sources
Petrović et al. (2024)	RAWEC, FANMA, SD	Evaluation of sustainability of transport modes
Krstić et al. (2015)	FANMA, VIKOR	Assessment of the economic sustainability of leading spas in Serbia
Dwivedi and Sarma (2025a)	ENTROPY, SWEI, TOPSIS	Evaluation of photovoltaic thermal collectors to increase energy efficiency in power systems
Dwivedi (2024)	SWI, SWEI	Material selection
Gligorić et al. (2024)	MAXC, TODIFFA	Evaluation of deep learning software tools for large-scale enterprises

2.3. Literature on the relationship between Logistics Performance Index (LPI) and Sustainable Development Goals (SDGs)

Vilalta-Perdomo et al. (2023) examined the impact of international logistics performance (LPI) on the United Nations' Sustainable Development Goal 2 (Zero Hunger) using mixed-effect regression models using data from 156 countries over the period 2016–2018. The study revealed that the LPI significantly and strongly impacted SDG2 achievement, particularly through the "customs" component. Qazi et al. (2024) developed a hybrid method that combines Bayesian Belief Networks (BBN) and Structural Equation Modeling (PLS) using Sustainable Development Goals (SDG) and Logistics Performance Index (LPI) data from 157 countries. The study determined that the goals of "industry, innovation, and infrastructure," "climate action," "partnerships for the goals," and "gender equality" had a significant impact on logistics performance. Rehman and Hassan (2025) empirically analyzed the impact of logistics performance on the Sustainable Development Goals (SDGs) using data from 2015–2024 for 126 countries. In the study, the Logistics Performance Index (LPI) was tested separately with each SDGs score using regression analysis, and it was observed that it had significant effects, particularly on SDG 7 (Clean and Affordable Energy), SDG 8 (Decent Work and Economic Growth), and SDG 9 (Industry, Innovation, and Infrastructure). Furthermore, it was revealed that this relationship varies according to the level of globalization and the development level of countries, and that globalization moderates the relationship between the LPI and the SDGs. Loucanova et al. (2024) examined the relationship between logistics performance and sustainability levels in 27 countries of the European Union, using correlation, clustering, and geographic analysis methods. They found a statistically significant and strong relationship between logistics performance and sustainability and identified clusters of countries with similarities based on geographical proximity. Khan et al. (2022) analyzed the effects of disruptions in the food supply chain on malnutrition in 15 Asian countries during the COVID-19 period using the panel data method, revealing the indirect effect of logistics performance on SDG2 (Zero Hunger). Kumar Singh et al. (2022) showed through mathematical modeling and fixed-point iteration that collection, separation, and recycling of electronic products through reverse logistics plays a critical role in reducing environmental impacts through logistics performance. Maheswari et al. (2020) showed that informal e-waste businesses in Indonesia play a critical role in reducing their environmental impact through reverse logistics and measuring their sustainable performance.

2.4. Research gaps and contributions to the literature

The existing literature largely focuses on either logistics performance (LPI) or sustainable development indicators (SDGs). Although several studies have examined the relationship between these two dimensions using different analytical approaches (Qazi et al., 2024; Loucanova et al., 2024; Rehman & Hassan, 2025; Vilalta-Perdomo et al., 2023), research that integrates LPI and SDG indicators within a unified and comprehensive methodological framework remains limited. In particular, no MCDM-based study has jointly evaluated both data sets at the country level, nor has any research simultaneously addressed logistics performance and sustainable development specifically for G20 countries. Existing studies generally adopt regional or global perspectives, leaving country-specific and comparative assessments for the G20 largely underexplored (Gelmez et al., 2024; Harsono & Wahyuningsih, 2023; Pehlivan et al., 2024). Moreover, the literature lacks integrated applications that combine SITDE, FANMA, SWEI, and TODIFFA methods, indicating a clear methodological and empirical gap.

Within this context, the methodological framework adopted in the present study makes a significant contribution to filling these gaps. The binary correlation analysis used to examine the linear relationships between LPI and SDG indicators provides an initial understanding of how the two indices interact. Subsequently, the objective determination of indicator weights through SITDE, the construction of integrated country rankings using FANMA, SWEI, and TODIFFA, and the aggregation of final results via the Borda count enable a balanced and simultaneous evaluation of logistics and sustainability performance. This study not only analyzes logistics efficiency and individual sustainability indicators but also provides a holistic perspective on the competitiveness of G20 countries in global trade and their contributions to sustainable development. The proposed framework provides policymakers and decision-makers with a reliable and comprehensive evidence base for infrastructure development, carbon reduction strategies, and sustainable development planning.

3. Dataset and method

This study examines the relationship between logistics efficiency and sustainable development by examining G20 countries. The analysis was conducted using the Logistics Performance Index (LPI) and Sustainable Development Indicators (SDGs). LPI data is for 2022, and SDG indicators were selected to be consistent with the LPI data, all for 2022. However, 2022 data for some sustainable development indicators for the Russian Federation, Saudi Arabia, and Argentina were not available. These countries were excluded from the analysis. As the missing SDG indicators for these countries were not fully available in the 2022 data sets, the application of data imputation techniques was deemed inappropriate. The use of estimated or artificially generated values could distort indicator weights, introduce bias into MCDM calculations, and undermine the reliability of country rankings. Therefore, to ensure methodological robustness and preserve cross-country comparability, the analysis was conducted only with G20 members whose datasets were complete and consistent. Therefore, an integrative analysis was conducted across 16 G20 countries; the relationships between SDG and LPI indicators were examined using binary correlation analysis, and countries' sustainability performance was assessed using multi-criteria decision-making approaches based on the integrated structure of these indicators. To ensure the integrity of the research, the Logistics Performance Index (LPI) indicators were analyzed in two different ways. First, both the LPI overall score and its sub-dimensions (LPI1–LPI6) were included in the correlation analysis. This approach enabled testing the relationships between logistics performance and sustainable development indicators (SDGs) at both holistic and dimensional levels. In the multi-criteria decision-making (MCDM) analysis conducted in the second stage, only the LPI sub-dimensions (LPI1–LPI6) were used to maintain a balance of weights among the indicators and to measure logistics performance in more detail. The LPI total score is derived from the LPI1–LPI6 sub-dimensions. Therefore, including both the overall score and the sub-dimensions in the analysis would create a double-counting effect, resulting in disproportionate weighting of the logistic variables. To prevent this and maintain a balanced weighting of the indicators, only the LPI sub-dimensions were used in the MCDM stage. Information on the indicators used in the analysis is presented in Tables 3 and 4, respectively. Table 5 presents the coefficient matrix for the relevant indicators for the G20 countries included in the analysis. Analyses were conducted using Microsoft Excel and SPSS Statistics software.

TABLE 3 | SDGs criteria included in the research

Criterion Code	Criteria
SDG 2.1	Prevalence of undernourishment (%)
SDG2.7	Cereal yield (tonnes per hectare of harvested land)
SDG2.10	Exports of hazardous pesticides (tonnes per million population)
SDG6.1	Population using at least basic drinking water services (%)
SDG6.2	Population using at least basic sanitation services (%)
SDG7.1	Population with access to electricity (%)
SDG12.1	Electronic waste that is not recollected (kg/capita)
SDG15.5	Imported deforestation (m2/capita)

TABLE 4 | LPI criteria included in the research

Criterion Code	Criteria
LPI1	Logistics performance index: Ability to track and trace consignments
LPI2	Logistics performance index: Competence and quality of logistics services
LPI3	Logistics performance index: Ease of arranging competitively priced shipments
LPI4	Logistics performance index: Efficiency of customs clearance process
LPI5	Logistics performance index: Frequency with which shipments reach consignee within scheduled or expected time
LPI6	Logistics performance index: Quality of trade and transport-related infrastructure
LPI	Logistics performance index: Overall

TABLE 5 | Decision matrix of countries' LPI and SDGs indicators

Country	LPI1	LPI2	LPI3	LPI4	LPI5	LPI6	LPI	SDG2.1	SDG2.7	SDG2.10	SDG6.1	SDG6.2	SDG7.1	SDG12.1	SDG15.5
Australia	4.100	3.900	3.100	3.700	3.600	4.100	3.700	2.500	2.900	43.100	100.000	100.000	100.000	11.200	11.200
Brazil	3.200	3.300	2.900	2.900	3.500	3.200	3.200	3.900	4.900	0.400	99.600	90.900	100.000	11.000	1.800
Canada	4.100	4.200	3.600	4.000	4.100	4.300	4.000	2.500	4.100	2.300	99.200	98.600	100.000	17.600	19.800
China	3.800	3.800	3.600	3.300	3.700	4.000	3.700	2.500	6.400	0.700	97.600	95.900	100.000	7.100	6.300
France	4.000	3.800	3.700	3.700	4.100	3.800	3.900	2.500	6.700	4.100	100.000	98.600	100.000	9.100	14.400
Germany	4.200	4.200	3.700	3.900	4.100	4.300	4.100	2.500	7.100	0.900	100.000	99.200	100.000	9.700	19.600
India	3.400	3.500	3.500	3.000	3.600	3.200	3.400	13.700	3.600	0.900	93.300	78.400	99.200	2.900	0.900
Indonesia	3.000	2.900	3.000	2.800	3.300	2.900	3.000	7.200	5.400	12.400	94.100	88.200	100.000	6.900	1.000
Italy	3.900	3.800	3.400	3.400	3.900	3.800	3.700	2.500	4.800	3.300	99.900	99.900	100.000	11.200	12.200
Japan	4.000	4.100	3.300	3.900	4.000	4.200	3.900	3.400	6.300	22.700	99.100	99.900	100.000	16.300	19.900
Korea, Rep.	3.800	3.800	3.400	3.900	3.800	4.100	3.800	2.500	6.600	1.300	100.000	99.800	100.000	9.400	17.100
Mexico	3.100	3.000	2.800	2.500	3.500	2.800	2.900	3.100	4.000	3.400	99.700	92.500	100.000	11.400	4.900
South Africa	3.800	3.800	3.600	3.300	3.800	3.600	3.700	8.100	5.000	86.800	94.500	77.600	86.500	8.400	2.800
Turkiye	3.500	3.500	3.400	3.000	3.600	3.400	3.400	2.500	3.500	1.500	97.000	99.200	100.000	10.500	7.000
United Kingdom	4.000	3.700	3.500	3.500	3.700	3.700	3.700	2.500	7.700	21.800	100.000	99.100	100.000	17.100	16.100
United States	4.200	3.900	3.400	3.700	3.800	3.900	3.800	2.500	8.100	12.300	100.000	99.600	100.000	9.300	18.600

Source: *World Bank (2022); Sachs et al. (2025)*

3.1. SITDE method

This method, designed by Gopisetty and Sama in 2024, addresses the limitations of traditional MCDM approaches by incorporating skewness as a critical factor in evaluating and weighting the criteria. The steps of this approach are detailed below (Gopisetty & Sama, 2025; Lava Kumar et al., 2025, pp. 5-6).

Step 1: Creating the decision matrix

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix}_{mxn} \tag{1}$$

At this stage, an X matrix representing the values of each alternative according to each criterion is created as in Equation (1). In this matrix, $X_{ij}>0$ must be true. If there are negative values, they must be converted to positive values using an appropriate method.

Step 2: Normalisation of the decision matrix

At this stage, the values in the decision matrix are reduced to an equal scale using the basic linear normalisation method. The elements of the normalised matrix are denoted by Z_{ij}^{x}. The normalisation process is performed using Equation (2).

$$Z_{ij}^{x} = \begin{cases} \dfrac{\min X_{kj}}{X_{ij}}, j \in J \\ \dfrac{X_{ij}}{\max X_{kj}}, j \in H \end{cases} \tag{2}$$

Here, J represents the set of benefit-oriented criteria, and H represents the set of cost-oriented criteria. On the other hand, X_{ij} represents the values in the decision matrix, while $minX_{kj}$ and $maxX_{kj}$ correspond to the minimum and maximum values of the relevant criterion.

Step 3: Calculating the skewness of the criteria

At this stage,

M :Total number of alternatives

Z_{ij}^{x}:Normalised value of alternative i for criterion j

$\overline{Z}_J$:Arithmetic mean of normalised values for criterion j

σ_j:Standard deviation of normalised values for criterion j

Accordingly, the skewness value K_j for criterion j is calculated using Equation (3).

$$K_j = \frac{M}{(M-1)(M-2)} \sum_{i=1}^{M} \left(\frac{Z_{ij}^{x} - \overline{Z}_j}{\sigma_j} \right)^3 \qquad (3)$$

Step 4: Normalisation of skewness values

The normalisation of skewness values obtained from distributions belonging to different criteria is performed using the transformation expressed in Equation (4).

$$LK_j = \log \left| \left((K_j + 1) + (|\min(K_j)| + 1) \right) \right| \qquad (4)$$

K_j: Skewness value of criterion j

$min(K_j)$: Smallest skewness value among all criteria

LK_j: Normalised skewness value for criterion j

Step 5: Calculating the criterion weights

The weight values for each criterion are obtained using Equation (5).

$$W_j = \frac{LK_j}{\sum_{j=1}^{n} LK_j} \qquad (5)$$

Here, LK_j denotes the normalised skewness value of the jth criterion, and n denotes the total number of criteria. $\sum_{j=1}^{n} LK_j$ denotes the sum of the normalised skewness values for all criteria.

3.2. FANMA method

In this study, the FANMA method was used not in the criterion weighting process but in the ranking of alternatives. The method measures the performance of alternatives based on the principle of distance from the ideal point and calculates each alternative's proximity to the ideal solution. In the first stage, the data in the decision matrix were normalised to the 0–1 range to ensure comparability. Subsequently, the deviation level of each alternative from the ideal solution was calculated based on the weighted normalised values, and the countries were ranked using the deviation values obtained. The FANMA method was preferred in this study because it ranks alternatives based on their distance from the weighted ideal solution, works with normalised data, and can be applied with criterion weights obtained using different weighting methods. The basic steps of the method are summarised below (Mandal et al., 2025, pp. 116–117):

Step 1: Creating the decision matrix

The decision matrix is created as shown in Equation (1).

Step 2: Normalising the elements in the decision matrix

The values in the matrix are normalised using Equation (6), taking into account the direction of the criteria.

$$a_{ij} = \begin{cases} \dfrac{x_{ij} - x_j^{\min}}{x_j^{\max} - x_j^{\min}}, j \in J \\ \dfrac{x_j^{\max} - x_{ij}}{x_j^{\max} - x_j^{\min}}, j \in H \end{cases} \; ; \; i = 1, 2, \ldots, m \;\; j = 1, 2, \ldots, n \qquad (6)$$

Here, $x_j^{\max} = \max\{x_{1j}, x_{2j}, \ldots, x_{mj}\}$ and $x_j^{\min} = \min\{x_{1j}, x_{2j}, \ldots, x_{mj}\}$.

Step 3: Determining the ideal point

The ideal point a_j^* for each criterion is determined according to Equation (7).

$$a_j^* = \begin{cases} \max\{a_{1j}, a_{2j}, \ldots, a_{mj}\}, j \in J \\ \min\{a_{1j}, a_{2j}, \ldots, a_{mj}\}, j \in H \end{cases} \qquad (7)$$

Step 4: Calculating and evaluating the deviation of each alternative from the ideal point

The deviation of each alternative from the ideal point is calculated using Equation (8).

$$g_i = \sum_{j=1}^{n} W_j^2 \left(a_j^* - a_{ij} \right)^2, \; i = 1, 2, \ldots, m \qquad (8)$$

W_j: Weight coefficient calculated using the SITDE method, representing the relative importance of each criterion.

The alternative with the smallest g_i value is identified as the best alternative.

3.3. SWEI method

The SWEI method was selected because it provides a quantitative framework for decision-making based on information theory, evaluating the desirability of alternatives through the probability–information content relationship. It enables the simultaneous analysis of different criteria by incorporating uncertainty directly into the decision-making process, and adapts a theoretical approach that is widely used in communication, statistics and decision theory for multi-criteria decision-making problems. These features give SWEI a general and flexible structure that can be applied to different MCDM problems, providing an alternative evaluation perspective to existing methods. The SWEI method process includes the following steps (Dwivedi & Sarma, 2025a, pp. 5-7).

Step 1: Creating the decision matrix

The decision matrix is created as in Equation (1).

Step 2: Normalising the decision matrix

Each element in the decision matrix is normalised according to the direction of the criteria using Equation (9), and a normalised decision matrix is created.

$$\overline{X_{ij}} = \begin{cases} \dfrac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}, j \in J \\ \dfrac{\frac{1}{x_{ij}}}{\sum_{i=1}^{m} \frac{1}{x_{ij}}}, j \in H \end{cases} \qquad (9)$$

Step 3: Calculating the weighted exponential information

In this step, the total amount of information for each alternative is calculated separately using exponential weighting, according to the previously specified criteria.

$$X_i'' = \sum_{j=1}^{n} \left(log_2 \left(\frac{1}{\overline{X_{ij}}} \right) \right)^{w_j} \qquad (10)$$

Here, W_j denotes the weight of criterion j obtained using the SITDE method, $\overline{X_{ij}}$ represents the normalised criterion value, and X_i'' represents the total information quantity of the ith alternative.

Step 4: Ranking the alternatives

Rank the alternatives using the calculated X_i'' values. The alternative with the smallest X_i'' value is the best, as it is closest to the ideal solution.

3.4. TODIFFA method

The TODIFFA method is an evaluation method that calculates the distance of each alternative from the optimal option using the hypotenuse function created from cost and benefit variables. The smaller this distance, the better the alternative is considered. The steps of the method are described below (Gligorić et al., 2024, pp. 3-9).

Step 1: Create the decision matrix.

The decision matrix is created using Equation (1).

Step 2: Normalising the decision matrix

The values in the matrix are normalized using the linear method, as expressed in equation (11).

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad \forall j \in [1, n] \qquad (11)$$

Step 3: Weighting the normalised decision matrix

Each element of the normalized decision matrix is multiplied by the corresponding criterion weight obtained from the SITDE method (Equation 5). This is done using equation (12).

$$q_{ij} = W_j.r_{ij} \quad \forall i \in [1,2,...,m],\ \forall j \in [1,2,...,n] \tag{12}$$

Step 4: Determining the optimal alternative

The optimal alternative consists of the following elements.

$$F^{opt} = [f_1^{opt}, f_2^{opt}, ..., f_j^{opt}],\ j \in [1,2,...,n] \tag{13}$$

The f_j^{opt} element is defined in relation to the desired target of the jth criterion. It is calculated using Equation (14).

$$f_j^{opt} = \begin{cases} \min_{i, \forall i \in \{1,2,...,m\}} (q_{ij} : j \in H) \\ \max_{i, \forall i \in \{1,2,...,m\}} (q_{ij} : j \in J) \end{cases} \tag{14}$$

Step 5: Separate the cost and benefit components of the alternatives.

Let h and $\ddot{J}$ represent the total number of cost and benefit criteria, respectively. Accordingly, the optimal alternative can be presented as the union of subsets of cost and benefit criteria.

$$F^{opt} = F_h^{opt} \cup F_{\ddot{j}}^{opt}, h + \ddot{j} = j \tag{15}$$

$$F^{opt} = [f_1^{opt}, f_2^{opt}, \dots, f_h^{opt}] \cup [f_1^{opt}, f_2^{opt}, \dots, f_{\ddot{j}}^{opt}], h + \ddot{j} = j \tag{16}$$

Similarly, the cost and benefit components of each alternative are shown in Equations (17)-(18).

$$F^i = F_h^i \cup F_{\ddot{j}}^i, \forall i \in \{1,2,\dots,n\}\ \ h + \ddot{j} = j \tag{17}$$

$$F^i = [q_1^i, q_2^i, \dots, q_h^i] \cup [q_1^i, q_2^i, \dots, q_{\ddot{j}}^i], \forall i \in \{1,2,\dots,n\}\ \ h + \ddot{j} = j \tag{18}$$

Step 6: Calculating the cost and benefit components for the alternatives.

Equations (19–22) calculate the magnitude of cost- and benefit-oriented components for the optimum alternative and other alternatives as the sum of their respective values under the relevant criteria.

For the optimal alternative

$$M_h^{opt} = f_1^{opt} + f_2^{opt} + \dots + f_h^{opt}, h \in H \tag{19}$$

$$M_{\ddot{j}}^{opt} = f_1^{opt} + f_2^{opt} + \dots + f_{\ddot{j}}^{opt}, \ddot{j} \in J \tag{20}$$

Similarly, for each alternative

$$M_h^i = q_1^i + q_2^i + \dots + q_h^i, \qquad \forall i \in [1,2,\dots,m], h \in H \tag{21}$$

$$M_{\ddot{j}}^i = q_1^i + q_2^i + \dots + q_{\ddot{j}}^i, \qquad \forall i \in [1,2,\dots,m], \ddot{j} \in J \tag{22}$$

Step 7: Ranking of alternatives

The ranking of alternatives is determined by the total differential of the alternative function, $f(M_h, M_{\ddot{j}})$.For all i in the set [1,2,…,m], the total differential of the alternative function at the point $(M_h^i, M_{\ddot{j}}^i)$ provides an approximate value for the change in the function at this point, given the changes in the variables M_h and $M_{\ddot{j}}$. Consequently, the total differential for each alternative is calculated using Equation (23).

$$dz_i = \frac{M_h^i(M_h^i - M_h^{opt}) + M_{\ddot{j}}^i(M_{\ddot{j}}^{opt} - M_{\ddot{j}}^i)}{\sqrt{(M_h^i)^2 + (M_{\ddot{j}}^i)^2}} \qquad \forall i \in [1,2,\dots,m] \tag{23}$$

The alternatives are arranged in ascending order of dz_i values, with the alternative with the lowest total differential value being considered the best.

3.5. Board counting method

The ranking results of different methods may vary in MCDM problems. Therefore, combining the results is beneficial in order to obtain a common ranking. The Borda Count method achieves this by combining different rankings to create a single final ranking. In this method, each alternative receives points according to its rank: the best alternative receives *m-1* points, the second-best alternative receives *m-2* points, and the worst alternative receives 0 points. The final ranking is determined by summing the scores obtained from all methods. The relevant method's mathematical formulation is given below (Unal, 2021, pp. 15–16; Wu, 2011, p. 12976).

Step 1: The board score for each alternative is calculated using Equation (24).

$$b_i = \sum_{j=1}^{n} (M - R_{ij}) \tag{24}$$

Here, M corresponds to the number of alternatives, and R_{ij} corresponds to the rank of the ith alternative according to the jth criterion.

3.6. Pearson correlation analysis

The Pearson correlation coefficient (r) is used to evaluate the strength of a linear relationship between two variables. It can take values between -1 and +1. A positive value indicates a positive linear correlation, while a negative value indicates a negative linear correlation. The closer the value is to +1 or -1, the stronger the linear correlation. The Pearson correlation coefficient is defined as follows (Fu et al., 2020, p. 2):

$$r = \frac{\sum_{i=1}^{n} [(x_i - \overline{x})(y_i - \overline{y})]}{\sqrt{\sum_{i=1}^{n} (x_i - \overline{x})^2} \sqrt{\sum_{i=1}^{n} (y_i - \overline{y})^2}} \tag{25}$$

Here, the variables x_i and y_i denote the means of the two variables, and n is the sample size. Generally, it is accepted that $r \leq 0.39$ represents weak correlations, r between 0.40 and 0.69 represents moderate correlations, r between 0.70 and 1 represents strong or high correlations, and $r \geq 0.9$ represents very high correlations.

4. Findings

This study adopted a two-stage analysis approach to enable a multidimensional assessment of the relationships between logistics performance and sustainable development. In the first stage, a Pearson correlation analysis was conducted to reveal the relationships between the Logistics Performance Index (LPI) sub-dimensions and the Sustainable Development Goals (SDGs) sub-indicators. The results are presented in Table 6.

According to the results of Pearson correlation analysis conducted to examine the bivariate relationships between the LPI and SDGs indicators, a positive and statistically significant relationship was found between the overall LPI score and SDG15.5 (imported deforestation) ($r = 0.804$; $p < 0.01$). Similarly, highly significant positive correlations were found between LPI sub-dimensions LPI1 (customs clearance efficiency), LPI4 (quality of logistics services), and LPI6 (on-time delivery) and SDG15.5 ($r = 0.829$, $r = 0.880$, and $r = 0.820$, respectively ($p < 0.01$). Significant positive relationships were found between LPI1 and SDG6.1 (access to basic drinking water services) at $r = 0.512$ ($p < 0.05$), and between LPI6 and SDG6.2 (access to basic sanitation services) at $r = 0.583$ ($p < 0.05$). Additionally, the correlation coefficient between SDG6.1 and SDG6.2 was $r = .836$ and this relationship was statistically significant ($p < 0.01$). SDG2.1 (undernutrition rate) was negatively correlated with all LPI indicators. Although these relationships were not statistically significant, the correlation between SDG2.1 and LPI6 was particularly high at $r = -0.483$ ($p = 0.058$). The relationships between SDG2.1 and SDG6.1 and SDG6.2 were $r = -.865$ and $r = -.899$ ($p < 0.01$), respectively. However, significant positive relationships were observed between SDG12.1 (hazardous chemicals and waste management) and SDG6.1 and SDG6.2 at $r = .602$ and $r = .576$, respectively ($p < 0.05$). No significant correlation was found between SDG7.1 (access to electricity) and the LPI indicators. Finally, quite high and significant correlations were found between the LPI sub-dimensions, for example, a relationship of r = .939 was found between LPI1 and LPI2 and r = .958 was found between LPI2 and LPI6 ($p < 0.01$).

In the second stage, the logistics and sustainability performances of the countries were evaluated holistically using the MCDM (SITDE, FANMA, SWEI, TODIFFA) methods. In this context, the overall LPI score in the decision matrix in Table 5 was removed, and a new decision matrix based solely on the sub-dimensions and SDGs indicators was used. The criteria weights were determined using the SITDE method (Equations 1–5) applied to the decision matrix, with the resulting values summarized in Table 7. Based on these weights, the logistics and sustainability performances of the alternative countries were assessed using the FANMA, SWEI, and TODIFFA methods, and the outcomes are reported in Table 8.

TABLE 6 | Correlation analysis results for LPI and SDGs indicators

Correlations		LPI1	LPI2	LPI3	LPI4	LPI5	LPI6	LPI	SDG2.1	SDG2.7	SDG2.10	SDG6.1	SDG6.2	SDG7.1	SDG12.1	SDG15.5
LPI1	Pearson Correlation	1	,939**	,681**	,908**	,804**	,915**	,946**	-,448	,431	,186	,512*	,541*	-,015	,389	,829**
	Sig. (2-tailed)		,000	,004	,000	,000	,000	,000	,082	,095	,489	,043	,030	,955	,137	,000
	N	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16
LPI2	Pearson Correlation	,939**	1	,716**	,920**	,866**	,958**	,973**	-,343	,306	,142	,406	,440	-,062	,375	,782**
	Sig. (2-tailed)	,000		,002	,000	,000	,000	,000	,194	,249	,599	,119	,088	,819	,152	,000
	N	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16
LPI3	Pearson Correlation	,681**	,716**	1	,615*	,735**	,624**	,796**	-,002	,387	,064	-,039	,086	-,228	-,034	,443
	Sig. (2-tailed)	,004	,002		,011	,001	,010	,000	,994	,139	,813	,885	,751	,395	,901	,086
	N	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16
LPI4	Pearson Correlation	,908**	,920**	,615*	1	,817**	,953**	,947**	-,412	,433	,077	,486	,553*	,076	,416	,880**
	Sig. (2-tailed)	,000	,000	,011		,000	,000	,000	,113	,094	,776	,056	,026	,780	,109	,000
	N	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16
LPI5	Pearson Correlation	,804**	,866**	,735**	,817**	1	,794**	,894**	-,353	,375	-,026	,444	,414	-,039	,376	,780**
	Sig. (2-tailed)	,000	,000	,001	,000		,000	,000	,179	,152	,925	,085	,111	,887	,151	,000
	N	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16
LPI6	Pearson Correlation	,915**	,958**	,624**	,953**	,794**	1	,948**	-,483	,356	,063	,496	,583*	,075	,396	,820**
	Sig. (2-tailed)	,000	,000	,010	,000	,000		,000	,058	,176	,818	,051	,018	,781	,129	,000
	N	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16
LPI	Pearson Correlation	,946**	,973**	,796**	,947**	,894**	,948**	1	-,351	,442	,111	,401	,454	-,053	,319	,804**
	Sig. (2-tailed)	,000	,000	,000	,000	,000	,000		,183	,086	,682	,123	,077	,847	,228	,000
	N	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16
SDG2.1	Pearson Correlation	-,448	-,343	-,002	-,412	-,353	-,483	-,351	1	-,327	,231	-,865**	-,899**	-,400	-,609*	-,622*
	Sig. (2-tailed)	,082	,194	,994	,113	,179	,058	,183		,217	,389	,000	,000	,125	,012	,010
	N	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16
SDG2.7	Pearson Correlation	,431	,306	,387	,433	,375	,356	,442	-,327	1	-,099	,347	,331	,093	,118	,528*
	Sig. (2-tailed)	,095	,249	,139	,094	,152	,176	,086	,217		,716	,188	,211	,732	,663	,036
	N	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16
SDG2.10	Pearson Correlation	,186	,142	,064	,077	-,026	,063	,111	,231	-,099	1	-,287	-,412	-,850**	,041	-,152
	Sig. (2-tailed)	,489	,599	,813	,776	,925	,818	,682	,389	,716		,280	,112	,000	,880	,575
	N	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16
SDG6.1	Pearson Correlation	,512*	,406	-,039	,486	,444	,496	,401	-,865**	,347	-,287	1	,836**	,471	,602*	,702**
	Sig. (2-tailed)	,043	,119	,885	,056	,085	,051	,123	,000	,188	,280		,000	,065	,014	,002
	N	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16
SDG6.2	Pearson Correlation	,541*	,440	,086	,553*	,414	,583*	,454	-,899**	,331	-,412	,836**	1	,649**	,576*	,765**
	Sig. (2-tailed)	,030	,088	,751	,026	,111	,018	,077	,000	,211	,112	,000		,007	,020	,001
	N	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16
SDG7.1	Pearson Correlation	-,015	-,062	-,228	,076	-,039	,075	-,053	-,400	,093	-,850**	,471	,649**	1	,182	,317
	Sig. (2-tailed)	,955	,819	,395	,780	,887	,781	,847	,125	,732	,000	,065	,007		,499	,231
	N	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16
SDG12.1	Pearson Correlation	,389	,375	-,034	,416	,376	,396	,319	-,609*	,118	,041	,602*	,576*	,182	1	,614*
	Sig. (2-tailed)	,137	,152	,901	,109	,151	,129	,228	,012	,663	,880	,014	,020	,499		,011
	N	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16
SDG15.5	Pearson Correlation	,829**	,782**	,443	,880**	,780**	,820**	,804**	-,622*	,528*	-,152	,702**	,765**	,317	,614*	1
	Sig. (2-tailed)	,000	,000	,086	,000	,000	,000	,000	,010	,036	,575	,002	,001	,231	,011	
	N	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

TABLE 7 | Weight values obtained as a result of the SITDE method

Criteria	LPI1	LPI2	LPI3	LPI4	LPI5	LPI6	SDG2.1	SDG2.7	SDG2.10	SDG6.1	SDG6.2	SDG7.1	SDG12.1	SDG15.5
w_j^{SITDE}	0.0683	0.0725	0.0691	0.0657	0.0515	0.0668	0.0908	0.0640	0.0925	0.0747	0.0813	0.1079	0.0535	0.0414
Ranking	9	6	7	10	13	8	3	11	2	5	4	1	12	14

According to Table 7, the three most important criteria are SDG7.1 (Population with access to electricity, w = 0.1079), SDG2.10 (Exports of hazardous pesticides, w = 0.0925), and SDG2.1 (Prevalence of undernourishment, w = 0.0908). Criteria with medium weight values include SDG6.1 (Population using at least basic drinking water services, w = 0.0747), SDG6.2 (Population using at least basic sanitation services, w = 0.0813), LPI2 (Logistics Performance Index: Competence and quality of logistics services, w = 0.0725), LPI1 (Ability to track consignments, w = 0.0683), LPI3 (Ease of arranging competitively priced shipments, w = 0.0691), LPI4 (Efficiency of customs clearance process, w = 0.0657), LPI6 (Quality of trade and transport-related infrastructure, w = 0.0668), and SDG2.7 (Cereal yield, w = 0.0640). The criteria with lower weights are SDG12.1 (Electronic waste not recollected, w = 0.0535), LPI5 (Frequency of shipments reaching the consignee within the scheduled or expected time, w = 0.0515), and SDG15.5 (Imported deforestation, w = 0.0414)

TABLE 8 | Ranking made with SITDE based FANMA, SWEI and TODIFFA methods

	FANMA		SWEI		TODIFFA	
Countries	g_i	Rank	X_i''	Rank	dz_i	Rank
Australia	0.0192	7	15.5623	**15**	0.01751	**15**
Brazil	0.0354	13	15.4069	2	0.01003	10
Canada	0.0191	**6**	15.4836	8	0.00612	**6**
China	0.0233	10	15.4058	1	0.00457	4
France	0.0188	5	15.4824	7	0.00426	2
Germany	0.0177	4	15.4191	3	0.00243	1
India	0.0371	**14**	15.4449	4	0.01592	**14**
Indonesia	0.0417	15	15.5453	**13**	0.01483	**13**
Italy	0.0214	**9**	15.4925	**9**	0.00654	7
Japan	0.0135	1	15.5497	14	0.01108	12
Korea, Rep.	0.0199	8	15.4464	5	0.00440	3
Mexico	0.0437	16	15.5325	**11**	0.01242	**11**
South Africa	0.0314	12	15.5965	**16**	0.04080	**16**
Turkiye	0.0306	11	15.4779	6	0.00898	8
United Kingdom	0.0162	2	15.5395	12	0.01000	9
United States	0.0172	3	15.5099	10	0.00529	5

According to the FANMA method, Japan, the United Kingdom, and the United States perform best, while Mexico, Indonesia, and India perform less well. The SWEI method ranks China, Brazil and Germany higher, while South Africa, Australia and Japan are lower. The TODIFFA method, on the other hand, ranks Germany, France and Korea higher, while South Africa, India, and Australia remain lower. In a comparative analysis, the ranking results of the SWEI and TODIFFA methods show closer trends. At the bottom, South Africa (16th), Mexico (11th), Indonesia (13th), and Australia (15th) are similarly positioned in both methods, while Germany and China are higher. On the other hand, the FANMA method differs from the SWEI and TODIFFA methods by exhibiting significant differences in rankings for countries such as Japan, the United Kingdom, and the United States. These findings reveal the impact of the methods' weighting and performance calculation logic on the ranking results and allow for a comparative assessment of countries' logistics and sustainability performance.

The Borda Counting Method was used to provide a comparable and holistic assessment of rankings obtained by different methods. This method combined the rankings obtained from the FANMA, SWEI, and TODIFFA analyses to reveal the overall performance of countries. Table 9 presents the rankings and corresponding Borda scores for each method separately. The final Borda scores and the resulting overall ranking were then calculated based on the sum of these scores. This allows for a more consistent and meaningful assessment of the relative positions among countries by aggregating the results from the different methods.

TABLE 9 | Combining the rankings of countries obtained from FANMA, SWEI and TODIFFA methods with the Borda Count method

	FANMA		SWEI		TODIFFA		BORDA	
Countries	Rank	Borda Score	Rank	Borda Score	Rank	Borda Score	Rank	Borda Score
Australia	7	9	15	1	15	1	13	11
Brazil	13	3	2	14	10	6	8,9,10	23
Canada	6	10	8	8	6	10	6	28
China	10	6	1	15	4	12	3	33
France	5	11	7	9	2	14	2	34
Germany	4	12	3	13	1	15	1	40
India	14	2	4	12	14	2	12	16
Indonesia	15	1	13	3	13	3	15	7
Italy	9	7	9	7	7	9	8,9,10	23
Japan	1	15	14	2	12	4	11	21
Korea, Rep.	8	8	5	11	3	13	4	32
Mexico	16	0	11	5	11	5	14	10
South Africa	12	4	16	0	16	0	16	4
Turkiye	11	5	6	10	8	8	8,9,10	23
United Kingdom	2	14	12	4	9	7	7	25
United States	3	13	10	6	5	11	5	30

Upon examination of the results, Germany ranks first with a total of 40 points, demonstrating the highest performance. France (34 points, 2nd place) and China (33 points, 3rd place) follow Germany. South Korea is fourth with 32 points, the United States is fifth with 30 points, and Canada is sixth with 28 points. The United Kingdom is in seventh place with 25 points, while Brazil, Italy, and Turkey share the eighth, ninth, and tenth places with 23 points each. Japan is eleventh with 21 points, India is twelfth with 16 points, Australia is thirteenth with 11 points, and Mexico is fourteenth with 10 points. Indonesia is fifteenth with 7 points, and South Africa is in last place (sixteenth) with only 4 points. These results show that the relative performance levels of countries are more clearly revealed by integrating the rankings obtained from different methods with the Borda approach. In particular, Germany, France, and China stand out with their high Borda scores; South Africa, Indonesia, and Mexico appear to be at the bottom of the rankings.

5. Conclusion

This study examines the relationships between logistics performance (LPI) and sustainable development indicators (SDGs) in G20 countries using an integrated approach. Due to data gaps, Russia, Saudi Arabia, and Argentina were excluded from the analysis, and the study was limited to the remaining 16 members of the G20. Bivariate correlation analysis reveals that logistics capacity is significantly related to various dimensions of sustainable development. A highly positive relationship was found between the overall LPI score and SDG 15.5 (imported deforestation). The strong positive relationships between the LPI sub-dimensions of customs clearance efficiency, logistics service quality, and on-time delivery, and SDG 15.5 can be explained by the fact that advanced logistics infrastructure streamlines the global supply chain, thereby creating indirect environmental impacts on agricultural and forest product production in other countries. This finding supports the close relationship between logistics performance and environmental sustainability indicators, as demonstrated in Lu et al. (2019). Additionally, significant positive relationships were observed between SDG 6.1 (access to basic drinking water services) and SDG 6.2 (access to basic sanitation services) and the LPI subscales. This result suggests that advanced logistics systems can increase the accessibility of water and sanitation services by ensuring the efficient distribution of materials and equipment necessary for these services. Similarly, a study by Brodny and Tutak (2023c) reveals that sustainable development indicators are closely related to logistics and infrastructure elements, supporting the notion that logistics capacity indirectly contributes to the social sustainability dimension.

Another noteworthy result is the negative correlation observed between SDG 2.1 (undernourishment rate) and the LPI indicators. This suggests that increasing logistics efficiency can reduce malnutrition by reducing disruptions in the food supply chain. Similarly, the very high negative correlations found between SDG 2.1 and SDG 6.1 and SDG 6.2 suggest that improving basic infrastructure services plays a critical role in combating hunger. The findings are consistent with existing literature. In particular, studies on the relationship between logistics performance (LPI) and the Sustainable Development Goals (SDGs) highlight the importance of these relationships. Vilalta-Perdomo et al. (2023) demonstrated that international logistics performance plays a critical role in achiving SDG2 (Hunger Elimination). The study examined the effects of logistics coordination at the regional level and the impact of the LPI on SDG2. Similarly, Khan et al. (2022) revealed that disruptions in the food supply chain can increase malnutrition rates, reinforcing the view that improving logistics efficiency helps mitigate these disruptions and thereby reduce malnutrition. In contrast, no significant relationship was observed between SDG 7.1 (access to electricity) and the LPI indicators. This suggests that the impact of energy infrastructure on logistics performance may be indirect and shaped by other factors. Limited positive relationships were found between SDG 12.1 (electronic waste and hazardous chemicals management) and the LPI, indicating the potential impact of sustainable logistics practices on environmental management. Indeed, studies on e-waste management and reverse logistics (Kumar Singh, 2022; Maheswari et al., 2020) emphasize that logistics plays a critical role in reducing environmental impacts, with logistics networks being particularly decisive in collection, recycling, and disposal processes. Furthermore, the positive relationships observed between SDG 12.1 and SDG 6.1 (basic drinking water services) and SDG 6.2 (basic sanitation services) confirm the mutually reinforcing nature of environmental and social sustainability indicators, as noted in Raman et al.'s (2024) study. This finding demonstrates that sustainable logistics can have positive impacts not only on environmental but also on social well-being.

Within the scope of the MCDM analysis, criteria were weighted using the SITDE method, and the priority levels of the LPI sub-dimensions and SDGs indicators were determined. The analysis determined that SDG 7.1 (access to energy) was the most important criterion, followed by SDG 2.10 (hazardous pesticide exports) and SDG 2.1 (malnutrition rate). Criteria with medium weights include water and sanitation services and logistics sub-dimensions. Criteria with lower weights consist of environmental sustainability indicators and some logistics measures. This weight distribution demonstrates that both social and environmental dimensions are considered in the performance evaluation of countries.

Ranking analyses conducted using the FANMA, SWEI, and TODIFFA methods reveal a heterogeneous picture of countries' logistics and sustainability performance. The FANMA method ranked Japan, the United Kingdom, and the United States highest, while Germany and France showed mid-to-upper results. In contrast, the SWEI method placed China and Brazil in the top two, highlighting differences when inter-criterion dependencies are considered. The TODIFFA method gave higher positions to Germany, France, and South Korea, whereas India, Indonesia, Australia, and South Africa performed lower. These differences indicate that the choice of weighting and calculation approaches significantly affects country rankings. To overcome such divergences, integrative approaches like the Borda Count method provide a more comprehensive assessment. Using this method, Germany ranked first with a total score of 40, followed by France and China in second and third place. South Korea, the United States, and Canada also performed strongly, while Brazil, Italy, and Turkey occupied middle positions. Japan, India, Australia, and Mexico were at the bottom, with South Africa showing the weakest performance. These findings suggest that integrated assessments such as the Borda Count are effective for identifying countries' strengths and weaknesses. The combined use of the FANMA, SWEI, and TODIFFA methods brings together the unique advantages offered by each method, enabling a more comprehensive and reliable assessment of countries' performance. This integration is methodologically robust compared to commonly used methods in the literature and enhances the interpretability of results, while also supporting the reliability of assessments conducted using the Borda Count.

Evaluating correlation analyses and MCDM ranking results together provides insight into the differences in the integrated performance of countries. Germany's high ranking aligns with its high World Bank Logistics Performance Index (LPI) scores (World Bank, 2022) and its strong performance on sustainable development indicators (Sachs et al., 2025). These high scores are supported by positive and significant correlations between Germany's LPI sub-dimensions (namely, the efficiency of customs procedures and on-time delivery) and SDG 6.1 and SDG 6.2 ($p < 0.05$). Positive but statistically insignificant correlations were observed between SDG12.1 and LPI sub-dimensions. This indicates that strong logistics performance is consistent with certain sustainable development indicators and enhances integrated performance. Conversely, in South Africa, which ranks lower, low scores on LPI sub-dimensions and SDGs indicators (World Bank, 2022; Sachs et al., 2025), combined with negative correlations between SDG 2.1 (undernourishment) and SDG 6.1 and SDG 6.2, explain the country's low integrated performance. These findings reveal that considering logistics performance and sustainable development indicators in an integrated manner plays a critical role in interpreting countries' rankings and understanding performance differences.

The results demonstrate that combining logistics performance (LPI) with the Sustainable Development Goals (SDGs) has significant policy implications. Based on the study's specific findings, recommendations include improving food supply chain security, using logistics effectively for water and sanitation services, promoting renewable energy for logistics centres, and expanding recycling logistics. Additionally, potential avenues for future research include comparing different MCDM methods, conducting in-depth country analyses and testing the robustness of results through time-series or regional comparisons.

However, the study has several limitations. First, its focus on G20 countries restricts generalizability to low- and middle-income nations. Second, reliance on data from a specific period limits the ability to capture long-term patterns or sudden shocks. Third, only the LPI and selected SDGs indicators were analyzed, excluding other relevant measures such as green logistics, carbon footprints, and e-logistics. Finally, while FANMA, SWEI, TODIFFA, and the Borda Count were applied, other MCDM methods were not considered.

Future studies should consider expanding the country scope and incorporating additional environmental and social indicators. Furthermore, the application of structural equation modelling (SEM) or panel causality tests, the examination of regional differences, and the use of simulations or alternative weighting scenarios could enhance the reliability of the results and policy recommendations. The correlation analyses conducted in this study only demonstrate relationships between variables and do not allow for direct inferences about causality to be made. Therefore, future studies would benefit from conducting Granger causality or panel regression analyses to test whether the observed relationships are causal, as this would strengthen the robustness of the findings. Additionally, although the criterion weights were objectively determined using the SITDE method, a sensitivity analysis was not conducted to evaluate how changes to these weights might affect the final ranking. Conducting a sensitivity analysis to evaluate the robustness of the results under various weighting scenarios would enhance the reliability of the findings in future studies.

References

Aboul-Dahab, K. M., & Ibrahim, M. A. (2020). Logistics Performance Index (LPI) and insights on the logistics performance improvement in the Arabian Region. *The International Journal of Business Management and Technology, 4*(2), 1-15.

Agrawal, R., Majumdar, A., Majumdar, K., Raut, R. D., & Narkhede, B. E. (2022). Attaining sustainable development goals (SDGs) through supply chain practices and business strategies: A systematic review with bibliometric and network analyses. *Business Strategy and the Environment, 31*(7), 3669-3687. https://doi.org/10.1002/bse.3057

Akhtar, M., Xu, J., Kashif, U., Ali, K., Muhammad Naveed, H., & Haris, M. (2025). Bayesian neural network modelling for estimating ecological footprints and blue economy sustainability across G20 nations. *Humanities and Social Sciences Communications, 12*(1), 1-14. https://doi.org/10.1057/s41599-025-04378-x

Asadikia, A., Rajabifard, A. & Kalantari, M. (2023). A systems perspective on national prioritisation of sustainable development goals: Insights from Australia. *Geography and Sustainability, 4*(3), 255-267. https://doi.org/10.1016/j.geosus.2023.06.003

Ayyildiz, E. (2022). Fermatean fuzzy step-wise Weight Assessment Ratio Analysis (SWARA) and its application to prioritizing indicators to achieve sustainable development goal-7. *Renewable Energy, 193*, 136-148. https://doi.org/10.1016/j.renene.2022.05.021

Biswas, S., & Anand, O. P. (2020). Logistics competitiveness index-based comparison of BRICS and G7 countries: An integrated PSI-PIV approach. *IUP Journal of Supply Chain Management, 17*(2).

Brodny, J., & Tutak, M. (2023a). Assessing the energy and climate sustainability of European Union member states: An MCDM-based approach. *Smart Cities, 6*(1), 339–367. https://doi.org/10.3390/smartcities6010017

Brodny, J., & Tutak, M. (2023b). The level of implementing sustainable development goal" Industry, innovation and infrastructure" of Agenda 2030 in the European Union countries: Application of MCDM methods. *Oeconomia Copernicana, 14*(1), 47-102. https://doi.org/10.24136/oc.2023.002

Brodny, J., & Tutak, M. (2023c). Assessing regional implementation of Sustainable Development Goal 9 "Build resilient infrastructure, promote sustainable industrialization and foster innovation" in Poland. *Technological Forecasting and Social Change, 195*, 122773. https://doi.org/10.1016/j.techfore.2023.122773

Campoli, J. S., Kodama, T. K., Nagano, M. S., & Burnquist, H. L. (2025). Progress of G20 nations on the 6th sustainable development goal under the circular economy perspective. *Journal of the Knowledge Economy*, 1-30. https://doi.org/10.1007/s13132-024-02475-x

Candan, G., & Toklu, M. C. (2024). Evaluating security performances of EU countries in the context of sustainable development using fuzzy SMART and ARAS approaches. *Environment, Development and Sustainability, 26*(1), 1645-1671. https://doi.org/10.1007/s10668-022-02779-5

Cheng, H., Chaudhry, H. R., Kazi, I., & Umar, M. (2024). Unlocking greener supply chains: A global innovative perspective on the role of logistics performance in reducing ecological footprints. *Journal of Innovation & Knowledge, 9*(4), 100612. https://doi.org/10.1016/j.jik.2024.100612

Dimitrijevska, D., Mihajlović, I., & Veličkovska, I. (2020). Logistic process indicator (LPI) as the measure of infrastructural and regional development. In *XV FIKUSZ 2020 International Conference: Symposium for Young Researchers* (pp. 5-23). Óbuda University. https://machinery.mas.bg.ac.rs/handle/123456789/5508

Dwivedi, P. P. (2024). *Multi-criteria decision making methods in terms of information measures* [Unpublished master's thesis]. Jaypee University of Engineering and Technology. http://hdl.handle.net/10603/595191

Dwivedi, P. P., & Sharma, D. K. (2025a). Quantitative assessment of photovoltaic thermal collectors to enhance energy efficiency in the power system by SWEI MCDM method. *Renewable and Sustainable Energy Reviews, 217,* 115791.

Dwivedi, P. P., & Sharma, D. K. (2025b). Performance measures of sustainable development goals using SWI MCDM methods: a case of the Indian states. *International Transactions in Operational Research,* (2025), 1-33. https://doi.org/10.1111/itor.13609

Ersoy, N., Özçalıcı, M., & Trung, D. D. (2026). A Hybrid MCDM Approach for SDGs Assessment of EU Countries. *Spectrum of Decision Making and Applications, 3*(1), 164-186. https://doi.org/10.31181/sdmap31202637

Fu, T., Tang, X., Cai, Z., Zuo, Y., Tang, Y., & Zhao, X. (2020). Correlation research of phase angle variation and coating performance by means of Pearson's correlation coefficient. *Progress in Organic Coatings, 139*, 105459.

Gelmez, E., Güleş, H. K., & Zerenler, M. (2024). Evaluation of logistics performances of G20 Countries using SD-based COPRAS and SAW methods. *Journal of Turkish Operations Management, 8*(2), 339-353.

Gligorić, Z., Görçün, Ö. F., Gligorić, M., Pamucar, D., Simic, V., & Küçükönder, H. (2024). Evaluating the deep learning software tools for large-scale enterprises using a novel TODIFFA-MCDM framework. *Journal of King Saud University-Computer and Information Sciences, 36*(5), 102079. https://doi.org/10.1016/j.jksuci.2024.102079

Gong, M., Teller, N., Golebie, E. J., Aczel, M., Jiang, Z., Van Zeghbroeck, J., & Liu, J. (2024). Unveiling complementarities between mangrove restoration and global sustainable development goals. *Journal of Cleaner Production, 474*, 143524. https://doi.org/10.1016/j.jclepro.2024.143524

Gopisetty, Y. B., & Sama, H. R. (2025). Skewness impact through distributional evaluation (SITDE) method: A new method in multi-criteria decision making. J*ournal of the Operational Research Society, 76*(6), 1204-1224. https://doi.org/10.1080/01605682.2024.2416910 (Published online 2024)

Hamidova, L., Alikhanova, L., Kasumova, L., Karimova, T., & Mirzayeva, F. (2024). The impact of CO_2 emissions from different types of transport on countries' logistics efficiency: Case of ITF member countries. *Environmental Economics, 15*(2), 215. http://dx.doi.org/10.21511/ee.15(2).2024.15

Harsono, M. I., & Wahyuningsih (2023). Logistics Performance And Other Factors As Antecedents Of The Sustainability Performance Of G-20 Countries. *International Journal of Economic Research and Financial Accounting, 2*(1). https://doi.org/10.55227/ijerfa.v2i1.54

Jayalakshmi, R., & Praveen, V. (2024). Assessing the influence of GDP and trade balance on logistics performance index (LPI): A cross-country analysis. *International Journal of Research in Human Resource Management, 6*(2), 339-345.

Jonasíková, D., Konečný, V., & Zuzaniak, M. (2025). Evolution of logistics performance index and their structure in selected countries. *Transportation Research Procedia, 87*, 217-231. https://doi.org/10.1016/j.trpro.2025.04.125

Kabak, Ö., Önsel Ekici, Ş., & Ülengin, F. (2020). Analyzing two-way interaction between the competitiveness and logistics performance of countries. *Transport Policy, 98*, 238-246. https://doi.org/10.1016/j.tranpol.2019.10.007

Khan, M. S., Aziz, G., Bakoben, H. B. M., & Saeed, A. (2025). Implications of sustainable logistics on economic, environment, and social dimensions: pre-and post-ımplementation of Saudi Vision 2030. *Journal of the Knowledge Economy*, 1-30. https://doi.org/10.1007/s13132-025-02616-w

Khan, S. A. R., Razzaq, A., Yu, Z., Shah, A., Sharif, A., & Janjua, L. (2022). Disruption in food supply chain and undernourishment challenges: An empirical study in the context of Asian countries. *Socio-Economic Planning Sciences*, *82*, 101033. https://doi.org/10.1016/j.seps.2021.101033

Krstic, B., Petrovic, J., & Stanišić, T. (2015). Analysıs of key indicators of economıc dimensions of Spas'sustainable development ın Serbia as tourism destinations. *Ekonomika*, *Journal for Economic Theory and Practice and Social Issues, 61*(3), 61-71. http://dx.doi.org/10.5937/ekonomika1503061K

Kumar Singh, S., Chauhan, A., & Sarkar, B. (2022). Supply chain management of e-waste for end-of-life electronic products with reverse logistics. *Mathematics, 11*(1), 124. https://doi.org/10.3390/math11010124

Larson, P. D. (2021). Relationships between logistics performance and aspects of sustainability: A cross-country analysis. *Sustainability, 13*(2), 623. https://doi.org/10.3390/su13020623

Lava Kumar, V., Kamruddin, S., Ventateswara Kumar, K. S., Kalvakolanu, S., Nalluri, V., & Chang, J. R. (2025). A multi-criteria decision-making approach to improve criteria ranking and weighting: integrating SITDE weighting with PIV and RAM techniques. *Asian Journal of Interdisciplinary Research, 8*(2). https://doi.org/10.54392/ajir2521

Li, J., Chen, X., Wang, W., Liu, W., De Maeyer, P., Van de Voorde, T., ... & Li, Y. (2025). Unraveling the differential ımpact pathways of landscape structures and ecosystem services on essential needs, governance, and objectives for Sustainable Development Goals (SDGs). *Sustainable Development, 3*(4). https://doi.org/10.1002/sd.3377

Liu, J., Yuan, C., Hafeez, M., & Yuan, Q. (2018). The relationship between environment and logistics performance: Evidence from Asian countries. *Journal of cleaner production, 204*, 282-291. https://doi.org/10.1016/j.jclepro.2018.08.310

Liu, Y., Lü, Y., Fu, B., & Zhang, X. (2023). Landscape pattern and ecosystem services are critical for protected areas' contributions to sustainable development goals at regional scale. *Science of the Total Environment, 881*, 163535. https://doi.org/10.1016/j.scitotenv.2023.163535

Loucanova, E., Kaputa, V., Nosalova, M., & Olsiakova, M. (2024). The logistics and sustainability in the European Union. *International Scientific Journal About Logistics*, *11*(2), 317-323. https://doi.org/10.22306/al.v11i2.515

Lu, M., Xie, R., Chen, P., Zou, Y., & Tang, J. (2019). Green transportation and logistics performance: An improved composite index. *Sustainability, 11*(10), 2976. https://doi.org/10.3390/su11102976

Maheswari, H., Yudoko, G., Adhiutama, A., & Agustina, H. (2020). Sustainable reverse logistics scorecards for the performance measurement of informal e-waste businesses. *Heliyon, 6*(9). https://doi.org/10.1016/j.heliyon.2020.e04834

Mandal, N., Sarkar, P., & Petrović, N. (2025). Multi-criteria decision-making for ranking renewable energy sources: A case study from the Republic of Serbia. *Journal of Engineering Management and Systems Engineering, 4*(2), 109-121. https://doi.org/10.56578/jemse040203

Mariano, E. B., Gobbo Jr, J. A., de Castro Camioto, F., & do Nascimento Rebelatto, D. A. (2017). CO2 emissions and logistics performance: a composite index proposal. *Journal of Cleaner Production*, *163*, 166-178. https://doi.org/10.1016/j.jclepro.2016.05.084

Martín, C. J., & Carnero, M. C. (2019). Evaluation of sustainable development in European Union Countries. *Applied Sciences, 9*(22), 4880.

Medina-Hernández, E. J., Guzmán-Aguilar, D. S., Muñiz-Olite, J. L., & Siado-Castañeda, L. R. (2023). The current status of the sustainable development goals in the world. *Development Studies Research, 10*(1), 2163677. https://doi.org/10.1080/21665095.2022.2163677

Mešić, A., Miškić, S., Stević, Ž., & Mastilo, Z. (2022). Hybrid MCDM solutions for evaluation of the logistics performance index of the Western Balkan countries. *Economics-Innovative And Economics Research Journal, 10* (1), 13-34. https://doi.org/10.2478/eoik-2022-0004

Özarı, C. (2025). Evaluation of the socio-economic performance of G-20 countries using the Critic-Aras method. *Third Sector Social Economy Journal, 60*(2), 1293-1310. http://dx.doi.org/10.63556/tisej.2025.1440

Pehlivan, P., Aslan, A. I., David, S., & Bacalum, S. (2024). Determination of logistics performance of G20 countries using quantitative decision-making techniques. *Sustainability, 16*(5), 1852. https://doi.org/10.3390/su16051852

Petrović, N., Jovanović, V., Marković, S., Marinković, D., & Petrović, M. (2024). Multicriteria sustainability assessment of transport modes: A European Union case study for 2020. *Journal of green economy and low-carbon development, 3*(1), 36-44. https://doi.org/10.56578/jgelcd030104

Qazi, A., Simsekler, M. C. E., & Al-Mhdawi, M. K. S. (2024). Bayesian network and structural equation modeling of dependencies between country-level sustainability risks and logistics performance. *Annals of Operations Research*, (2024), 1-28. https://doi.org/10.1007/s10479-023-05723-6

Raman, R., Lathabai, H. H., & Nedungadi, P. (2024). Sustainable development goal 12 and its synergies with other SDGs: identification of key research contributions and policy insights. *Discover Sustainability, 5(*1), 150. https://doi.org/10.1007/s43621-024-00289-0

Rashidi, K., & Cullinane, K. (2019). Evaluating the sustainability of national logistics performance using Data Envelopment Analysis. *Transport Policy, 74*, 35-46. https://doi.org/10.1016/j.tranpol.2018.11.014

Rehman, S., & Hassan, H. (2025). Empirical assessment of national logistics performance and its impact on advancing the Sustainable Development Goals: A global analysis [Preprint]. SSRN. https://doi.org/10.2139/ssrn.5200258

Sachs, J. D., Lafortune, G., Fuller, G., & Iablonovski, G. (2025). Financing sustainable development to 2030 and mid-century: Sustainable Development Report 2025. Paris: SDSN; Dublin: Dublin University Press. https://doi.org/10.25546/111909

Shamout, M. D. (2024). Towards a cleaner and sustainable Europe and Central Asia: An investigation of the logistics-environment nexus. *Sustainable Development, 32*(6), 6629-6642. https://doi.org/10.1002/sd.3055

Sheikh, W., Chowdhury, M. M. H., & Mahmud, K. K. (2023). A comprehensive performance measurement model for maritime Logistics: Sustainability and policy approach. *Case Studies on Transport Policy, 14*, 101097. https://doi.org/10.1016/j.cstp.2023.101097

Stanujkic, D., Popovic, G., Zavadskas, E. K., Karabasevic, D., & Binkyte-Veliene, A. (2020). Assessment of progress towards achieving Sustainable Development Goals of the "Agenda 2030" by using the CoCoSo and the Shannon Entropy methods: The case of the EU Countries. *Sustainability, 12*(14), 5717. https://doi.org/10.3390/su12145717

Starostka-Patyk, M., Bajdor, P., & Białas, J. (2024). Green logistics performance index as a benchmarking tool for EU countries environmental sustainability. *Ecological Indicators*, *158*, 111396. https://doi.org/10.1016/j.ecolind.2023.111396

Stević, Ž., Ersoy, N., Başar, E. E., & Baydaş, M. (2024). Addressing the global logistics performance index rankings with methodological insights and an innovative decision support framework. *Applied Sciences, 14*(22), 10334. https://doi.org/10.3390/app142210334

Suki, N. M., Suki, N. M., Sharif, A., & Afshan, S. (2021). The role of logistics performance for sustainable development in top Asian countries: Evidence from advance panel estimations. *Sustainable Development*, 29, 595–606. https://doi.org/10.1002/sd.2160

Thanyawatpornkul, R. (2024). Artificial ıntelligence-driven solution for global challenges: A systematic review from sustainable development goals perspectives. *Nternational Journal of Business Management and Economic Research (IJBMER), 15*, 3-27.

Unal, Y. (n.d.). *Using the GMM method as an alternative approach for clustering Hdi 2021 data and evaluation with CRITIC-based MCDM methods.* (Working Paper). http://dx.doi.org/10.2139/ssrn.4742720

Varma, S., & Shah, B. (2021, August 16–18). A study of the relationship between logistics performance and human development. In *Proceedings of the International Conference on Industrial Engineering and Operations Management* (pp. 833–845). IEOM Society International.

Vilalta-Perdomo, E., Michel-Villarreal, R., Thierry-Aguilera, R., Krejci, C., Rainer, J., & Burgos, D. (2023). The impact of logistics performance on the achievement of the UN Sustainable Development Goal 2: Zero hunger. *Center for Open Science*, 1-24. https://doi.org/10.31235/osf.io/3ykgx

Wan, B., Wan, W., Hanif, N., & Ahmed, Z. (2022). Logistics performance and environmental sustainability: Do green innovation, renewable energy, and economic globalization matter? *Frontiers in Environmental Science, 10,* 996341. https://doi.org/10.3389/fenvs.2022.996341

World Bank. (2022). Logistics Performance Index (LPI). https://data.worldbank.org/indicator/LP.LPI.OVRL.XQ

Wu, W. W. (2011). Beyond Travel & Tourism competitiveness ranking using DEA, GST, ANN and Borda count. *Expert Systems with Applications, 38*(10), 12974-12982.

Zaman, K., & Shamsuddin, S. (2017). Green logistics and national scale economic indicators: Evidence from a panel of selected European countries. *Journal of cleaner production, 143*, 51-63. https://doi.org/10.1016/j.jclepro.2016.12.150